The Halloween Effect: The Impact of Individual Stocks in Germany

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Abstract

The Halloween effect, the tendency that stocks perform better between November 1 and April 30 than in the other months of the year, has been a huge puzzle since its discovery in 2002. Various authors have examined the existence and the causes of this fascinating effect over the past two decades. These authors mainly investigated the Halloween effect considering stock indices. Although research on this macro level is important, very few authors looked closer at the Halloween effect by considering the individual stocks that are included in the stock indices. That's why this paper sheds another light on the Halloween effect by considering the individual stocks of one of the most important European indices, the DAX 30. The results show that almost all analyzed stocks, 32 of the 33, followed the Halloween effect pattern in Germany. However, the results also reveal that only 4 of the 33 analyzed companies show a (much) more significant Halloween effect than the DAX 30 itself. This may imply that the Halloween effect is driven by only a handful of companies in Germany. Moreover, the results show that smaller companies are more heavily affected by the Halloween effect than larger companies.

Keywords: Behavioral Finance; Halloween effect; Market efficiency; Stock market; DAX 30

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1. Introduction

The old market saying ''Sell in May and go away'' suggests selling stocks in May. The Financial Times already mentioned this market wisdom in 1935[1] (Zhang & Jacobsen, 2021). An old broker confirmed in a more recent article in The Telegraph in 2005 that he remembers brokers using the saying at the time[2]. According to him, 'it was always sell in May'. The idea behind this is to sell stocks in May and buy them back in the winter, because stocks drop in value in the summer months and increase in value in the winter months. This would contradict Nobel Prize winner Fama (1970) and his famous Efficient Market Hypothesis. He argued that it should be impossible that stock prices can be predicted like this. However, market anomalies such as the Sell-in-May anomaly provide evidence that this actually is possible and therefore, stock prices can be predicted.

Bouman & Jacobsen (2002) were the first to document the Sell-in-May anomaly, more widely known as the Halloween effect. They found it in 36 out of the 37 countries over the period January 1970 to August 1998. Andrade et al. (2013) confirmed these results. They studied the same sample of countries over the period 1998 to 2012 and found that the average winter return is 10 percent higher than the average summer return. In contrast, Maberly & Pierce (2004) argued that the results of Bouman & Jacobsen (2002) were mainly driven by a stock market crash in October 1987 and the bankruptcy of an important investment fund in August 1998. As both outliers happened in summer months, the Halloween effect might be driven by these two events. However, Witte (2010) replied that dropping the four next most influential outliers increased the Halloween effect again by over 12 basis points. Some other studies (e.g. Siriopoulos & Giannopoulos, 2006; Lucey & Zhao, 2008; Dichtl & Drobetz, 2015) also questioned the Halloween effect. Zhang & Jacobsen (2021) argued that these contradictory findings may be a result of sample selection. In their most recent work, they showed that the Halloween effect is a worldwide phenomenon. By using all available historical data on all stock market indices, they showed that the average return is higher in the winter than in the summer for 87 out of 114 countries, while statistically significant in 42 cases. For now, this research seems to answer all the sceptics that caused doubt on the existence of the Halloween effect.

There is one thing that all the previously mentioned studies have in common: they investigated the Halloween effect using stock indices. This is no coincidence. Almost all existing research focused on this macro level, without paying attention to individual stocks that are included in the particular index. Arendas et al. (2018) approached it differently. They recognized that it is interesting to analyze the Halloween effect on the individual stocks level, as numerous questions can be answered by doing so. Their most important result is that Halloween effect-based investment strategies should not only been related to stock indices, as suggested by many authors (e.g. Bouman & Jacobsen, 2002; Haggard &

[1] A written mention of the old market saying can be found in the Financial Times of Friday 10 of May 1935: ''*A shrewd North Country correspondent who likes stock exchange flutter now and again writes me that he and his friends are at present drawing in their horns on the strength of the old adage 'Sell in May and go away'.*''
[2] https://www.telegraph.co.uk/finance/2914779/Should-you-sell-in-May-and-buy-another-day.html

Witte, 2010; Lloyd et al., 2017), but also to individual stocks that experience a significant Halloween effect[3]. Their study is one of the few, if it is not the only, that investigates a certain index on the micro level. Motivated by this gap in the literature, this paper takes a closer look at the Halloween effect. It investigates to what extent individual stocks of one of the most important European indices, the German DAX 30, are affected by the Halloween effect. For this purpose, 33 stocks that have been included in the DAX since 1988 are analyzed. Different statistical tests, such as the t-test and Wilcoxon rank-sum test, are performed to do the analysis. This already extents existing literature. Furthermore, such micro level research allows for a deeper investigation of all individual stocks. It could be that the Halloween effect is concentrated in a certain type of stocks. For example, CAPM predicts that high beta stocks should earn higher returns to compensate investors for bearing a higher risk. Therefore, high beta stocks may differ from low beta stocks in terms of their winter returns. Again, such research has been conducted mostly on the macro level[4]. That's why this paper also investigates several different stock characteristics, namely the beta, size and book-to-market ratio, to further determine where the Halloween effect is concentrated.

The findings of this paper accelerate the need to take a closer look at stock indices when investigating the Halloween effect. It is found that almost all analyzed stocks, 32 of the 33, followed the Halloween effect pattern in Germany. This is what is expected, because the stock index itself also strongly follows the Halloween effect pattern. However, the results also reveal that only 4 analyzed companies show a more significant Halloween effect than the DAX 30 itself. This may imply that the Halloween effect is driven by only a handful of companies in Germany. Furthermore, the results show that smaller companies are more heavily affected by the Halloween effect than larger companies. No relationship is found between the Halloween effect and both the beta and book-to-market ratio. These findings could have serious implications for investors, since it seems even more profitable to invest in highly significant stocks that follow the Halloween effect pattern in comparison to a stock index.

This paper continues as follows. Chapter 2 will provide an overview of the most noticeable literature regarding the EMH, market anomalies in general, existence of the Halloween effect, explanations of the Halloween effect and how it is possible to profit from the Halloween effect. Hereafter, Chapter 3 will provide the research problem and hypotheses. Chapter 4 will provide the data and research methodology used. Chapter 5 handles the results of this paper. Finally, Chapter 6 concludes and discusses the findings. After that, the references and the appendix are presented.

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[3] For example, they found that Walt Disney experienced the Halloween effect in 78.38% of the investigated years, and the average return difference between the summer months and winter months equaled 20.72 percentage points.

[4] See for instance, Jacobsen & Visaltanachoti (2009)

2. Literature review

This chapter provides an overview of the literature related to the Halloween effect. First, the Efficient Market Hypothesis (hereafter EMH) is discussed. If markets are efficient, the Halloween effect cannot exist, and it would not be possible to outperform the market following a Halloween effect-based investments strategy. After that, market anomalies and the concept of data mining is discussed. This is followed by studies that investigated the existence of the Halloween effect and its sceptics. After that, potential explanations of the effect are discussed. The literature review concludes to point out whether it is profitable to follow Halloween effect-based investments strategies.

2.1 The Efficient Market Hypothesis

Seasonal anomalies have attracted the interest of financial economists for more than 50 years now. One reason for this interest is that anomalies, such as the Halloween effect, questions one of the most important hypotheses in the world of finance, the EMH. Fama (1970) first defined an efficient market. He argued that markets are efficient if prices, at any point in time, fully reflect all available information. In other words, stocks prices cannot be predicted, and abnormal returns cannot be achieved. The famous hypothesis can be divided into three different forms. According to the EMH, abnormal returns cannot be earned by using either historical information (weak form EMH), publicly available information (semi-strong EMH) or insider information (strong form EMH).

The weak form and semi-strong form of the EMH were widely accepted at the time. Generally, the strong form of the EMH is not supported by literature. According to Grossman & Stiglitz (1976), markets cannot be strong form efficient. Their paradox goes as follows. If even insider information is reflected in the price, no one would gather information to trade. In that case, it is impossible that all information is reflected in the price, because no one gathers information. Since the rise of behavioral finance beginning in the 1990s, the weak form and semi-strong form are questioned as well (Yen & Lee, 2008). Behavioral economists argue that cognitive and emotional biases lead to anomalies in market prices. Market anomalies challenge the EMH as they provide evidence that abnormal returns can be achieved by using financial reports (violates the semi-strong form) and by using historical information from stock markets (violates the weak form). In short, this school argues that markets are more often inefficient than they are efficient[5]. Some authors disagreed. A highly cited study by Malkiel (2003) showed that stock markets are actually far more efficient and less predictable than some behavioral economists often say. Fama (1998) argued that market efficiency survives the literature on anomalies. He pointed out that it is possible that anomalies are found purely due to the methodology used, and that most of them disappear after more reasonable techniques are applied. Empirical research also founded contradictory results. Some authors argued that the weak form EMH is supported by data (e.g. Konak & Şeker, 2014), others found mixed results (e.g. Borges, 2010) and some found no evidence that stock prices follow a random walk and rejected the weak form EMH (e.g. Hamid et al., 2017). There seems

[5] For an extensive view of behavioral finance on (in)efficient markets, see Schleifer (2000)

to be one general consensus here, which is that developed markets are more efficient than emerging markets (e.g. Cajueiro & Tabak, 2004; Risso, 2009). This can be explained by the fact that on average, developed markets are less volatile and therefore, new information is integrated more efficiently.

2.2 Market Anomalies

According to Schwert (2003), anomalies are empirical results that deviate from theories of asset-pricing behavior. He argued that anomalies could indicate that markets are not efficient. However, he also argued that most anomalies tend to disappear after they have been published in the academic world. Malkiel (2003) agreed that anomalies tend to vanish after they have received considerable attention. However, the next section provides evidence that suggests otherwise. Anomalies can be classified in two different categories: calendar anomalies and weather anomalies. An example of a weather anomaly is the temperature anomaly examined by Cao & Wei (2005). They found a significant, negative correlation between temperature and stock market returns, no matter what temperature it is. Alongside the Halloween effect, another famous example of a calendar anomaly is the January effect first examined by Wachtel (1942). He found that stock returns are significantly higher in January in comparison to other months of the year.

Sullivan et al. (2001) argued that the finding of anomalies may simply be a result of data mining. They used a bootstrap method that measured the distortions induced by data mining and concluded that, once corrected for data mining, calendars effects are not significant anymore. Schwert (2003) agreed and described that many behavioral economists are worried that this concept could potentially undermine a huge number of findings regarding calendar effects. When authors want to investigate a certain phenomenon, it is likely that they focus on 'surprising' results. If subsequent authors examine more or less the same dataset and also find the same results, it seems like there is more evidence in favor of the anomaly, while actually there is not. Schwert (2003) proposed one solution. He argued to test the anomaly only on independent samples. This means that researchers should investigate other countries in other time periods to reduce the potential problem of data mining. As time goes by, the analysis of newly available data also provides a test of the anomaly.

2.3 The existence of the Halloween effect

The market anomaly this paper investigates is the Halloween effect: the tendency that stocks perform better between November 1 and April 30 (hereafter also defined as winter) than in the other months (hereafter also defined as summer). Bouman & Jacobsen (2002) were the first to document this calendar effect. They investigated 37 different countries and illustrated that the chance of finding the Halloween effect in every country, assuming market efficiency and independent stock markets, equals $0.5^{37} = 0{,}73*10^{-12} = 0{,}00000000000073$. However, they actually found the Halloween effect in all countries, with the only exception being New Zealand. After this study, numerous other researchers investigated the Halloween effect as well. This section provides an overview of these studies. After that, the authors that questioned the existence of the Halloween effect will be discussed alongside the answers to these criticisms.

The Halloween effect became publicly known with a study from Bouman & Jacobsen (2002). They investigated 37 countries all around the world over the period 1970 to 1998. For all countries except one, they found higher stock market returns during the winter than during the summer. Out of these countries, 20 were also significant. Andrade et al. (2013) investigated the same sample, but over a newer time period, 1998 to 2012. They confirmed the results and concluded that the average winter return is 10 percentage points higher than the average summer return. Lloyd et al. (2017) investigated whether the Halloween effect is still present even after the global financial crises of 2008. Given the magnitude of this crisis, it could be that the Halloween effect would not survive in such turbulent times. However, the authors confirmed the existence of the Halloween effect and found it to be present in 34 out of the 35 investigated countries. Jacobsen & Visaltanachoti (2009) focused on differences between sectors instead of countries. They investigated the Halloween effect in 17 different sectors and 49 different industries in the U.S. The authors found that all sectors have higher winter returns than summer returns. However, maybe even more interesting is that there are relatively large differences between sectors. For example, there is a weak Halloween effect in consumer sectors, while production sectors experience a much stronger Halloween effect on average. Geographically, the Halloween effect is relatively strong in countries located in Europe, North America and Asia compared to other areas according to Zhang & Jacobsen (2021). Another interesting finding from their study is that developed markets and emerging markets seem to experience a stronger Halloween effect than frontier markets and rarely studied markets. However, they pointed out this might be caused by the limited availability of data for such markets. Swagerman & Novakovic (2010) confirmed that the Halloween effect is present in both developed and emerging markets, although stronger in the former.

There are also some studies that caused doubt on the existence of the Halloween effect. Maberly & Pierce (2004) criticized the results of Bouman & Jacobsen (2002). They argued that the Crash of October in 1987 and the collapse of the hedge fund Long-Term Capital Management in August 1998 were the drivers of the findings, because these two events both happened in summer months. However, Witte (2010) found that dropping not only these two outliers, but the four next most influential outliers as well, increased the Halloween effect again by over 12 basis points. He eventually showed that the Halloween effect is statistically significant on the U.S. stock market. Lucey & Zhao (2008) investigated the U.S. stock market over the period 1926 to 2002 by looking at 20-year sub-periods. They found that the Halloween effect is generally not present and when it does appear, it is only a result of the January effect. However, Haggard & Witte (2010) showed that these findings are likely to be the result of the small sample size used. They used larger subperiods and updated the same data until 2008 to show that the Halloween effect is present over the period 1954 to 2008, statistically significant and independent of the January effect. They only confirm that there is no Halloween effect present over the period 1926 to 1953. A study by Siriopoulos & Giannopoulos (2006) suggested that the Halloween effect might be driven by data outliers. They found there is no Halloween effect on the Greek stock exchange after controlling for the impact of outliers over the period October 1986 to December 2004. Dichtl & Drobetz

(2015) even argued that the Halloween effect strongly weakened or even seem to have disappeared in some markets. The study by Zhang & Jacobsen (2021) seem to answer all the sceptics once and for all by using all available historical data (62962 monthly observations) on all stock market indices worldwide. They found that the 6-month return during the winter is on average 4% higher than during the summer. The mean returns are higher in the winter for 89 out the 114 investigated countries. This is statistically significant in 42 countries, while only the country Mauritius shows significantly higher summer returns. The authors argue that it is likely that the contradictory findings that have been presented are a result of sample selection. For now, this research seems to answer all the sceptics.

2.4 Explanations of the Halloween effect

It is now clear that a wide variety of studies found evidence of the Halloween effect. Fama (1998) argued that long-term market anomalies tend to disappear, because markets become efficient. He argued that it is unlikely that such anomalies persist over a long period of time. However, the Halloween effect exists for quite some years now and does not seem to weaken since its discovery (Zhang & Jacobsen, 2021). This raises the question where the Halloween effect comes form. How can it be that winter returns are higher than summer returns? Several studies have tried to answer this question. This section provides an overview of potential explanations of the Halloween effect. First, the data mining problem and findings of Bouman & Jacobsen (2002) are discussed. After that, behavioral, weather and other explanations are discussed.

Maberly & Pierce (2004) claimed that the Halloween effect is attributable to data mining. As discussed, it is possible that anomalies are simply a result of data mining (Sullivan et al., 2001; Schwert, 2003). However, Bouman & Jacobsen (2002) argued that it is unlikely that this holds for the Halloween effect as well. They agreed that other anomalies such as the January effect and Monday effect may well be caused by data mining, as there was no indication of any theory that suggested high returns can be made in January or on Mondays prior to the effect was found. The Halloween effect is different in that sense, as indications of the effect, the old market saying, date back to as far as 1935. This makes it less likely that data mining plays a role. Secondly, Schwert (2003) proposed to test the anomaly on independent samples to see if data mining may explain the anomaly. The recent work of Zhang & Jacobsen (2021) showed that the anomaly exists in a lot of different countries over a lot of different periods, making it even more unlikely that data mining has something to do with the Halloween effect.

Bouman & Jacobsen (2002) considered several other possible explanations without any result. They investigated whether higher winter returns are simply a compensation for higher risk during this period. If that is the case, the standard deviation should be considerably higher in the winter compared to the summer. However, this measure of risk tends to be very similar in the winter and the summer. There are a few countries with a slightly higher risk in the winter, but it is simply not high enough to serve as a plausible explanation of the Halloween effect. For example, an increase in risk of only 0.2 percent in the Swedish stock market would imply that investors need to be compensated by more than 25 percent in risk premia. Therefore, the authors rejected risk as an explanation. Carrazedo et al. (2016) agreed that the effect cannot be explained by risk. In addition, Bouman & Jacobsen (2002) also rejected that the January effect has anything to do with the Halloween effect. As the January effect states that returns are higher in January than in other months of the year, it could influence the Halloween effect. That's why the authors considered another regression which included a January dummy. They investigated the same 37 countries and found that 14 countries remained significant after controlling for the January effect instead of 20 countries without doing so. The authors stressed that they overstated the size of the January effect and understated the size of the Halloween effect in this regression, because they assumed that all excess returns in January are because of the January effect and not because of the Halloween effect. Other authors agreed that the Halloween effect is independent of the January effect (e.g. Haggard & Witte, 2010; Carrazedo et al., 2016). Bouman & Jacobsen (2002) also found that the introduction of transaction costs, shifts in either interest rates or trading volume and a seasonal factor in the provision of news cannot explain the anomaly.

Bouman & Jacobsen (2002) did find one possible explanation that remains getting support to date. They showed that the Halloween effect is significantly related to the length and the timing of summer vacations as well as to the impact of summer vacations on trading activity in different countries. They argued that the Halloween effect is most present in countries with a strong tradition of summer vacations. This vacation hypothesis might be caused by liquidity constraints of investors. As investors, just like other people, spend relatively more money during summer vacations, they may demand a higher liquidity premium during the winter months. An alternative explanation could be that summer vacations lead to changes in risk aversion of investors, which causes summer stock returns to drop. One problem with this link is that arbitrageurs would realize that there are arbitrage possibilities and make the effect go away. Although this is a forceful issue, they ultimately cannot reject this vacation hypothesis. Hong & Yu (2009) also linked stock returns to summer vacations, but considered only three summer months[6]. Despite this difference, they also found lower stock returns in the summer for most countries, because trading activity falls during the summer as investors are on vacation. Kaustia & Rantapuska (2016) came with a similar interesting finding. They investigated stock trading data from all investors in Finland and found that the monthly trading patterns of investors are in line with the vacation hypothesis. Investors sell stocks before vacation and trade less during vacation. It might be that investors want to finance their vacation consumption, don't want to stress about their investments or simply need mental closure. Jacobsen et al. (2019) investigated 34 different countries and also found evidence for the vacation hypothesis to be the explanation of lower summer returns, in particular for European countries. It seems like the vacation hypothesis is able to explain at least a part of the Halloween effect puzzle.

[6] They defined summer months as July, August and September for countries in the Northern Hemisphere and January, February and March for countries in the Southern Hemisphere.

Kamstra et al. (2003) found a possible multidisciplinary explanation of the Halloween effect. They linked a famous concept in psychology, Seasonal Affective Disorder (hereafter SAD), to stock market returns. SAD is a type of depression that is related to changes in seasons. It affects people during seasons with relatively fewer hours of daylight. According to the authors, many experimental psychology studies indicate a link between depression and higher risk aversion. They found evidence of a strong SAD effect that leads to seasonal cycles in stock market returns around the world. To be more specific, stock market returns should be lower during fall when investors may feel depressed, which causes a higher risk aversion. As days start to get longer, which happens after December 21st or 22nd in the Northern Hemisphere, the mood of investors improves, and their risk aversion decreases again. Kamstra et al. (2017) agreed that investors tend to become more risk averse in the fall, and less risk averse in the winter and spring. This peaks in March, the month that is associated with the highest recovery of SAD. Ultimately, this reasoning leads to relatively higher returns during most Halloween months. Jacobsen & Marquering (2008) revisited this SAD link to stock market returns. They showed that it is premature to argue that the Halloween effect is caused by a change in the mood of investors. Although they agreed that SAD is correlated with stock market returns, they pointed out that this not necessarily mean that the relation is also one of causation. Kelly & Meschke (2010) were also sceptic about the SAD anomaly. They showed that Kamstra et al. (2003) modelled several assumptions about psychological behavior in the wrong way which led to a link that may actually not be there.

Hirshleifer et al. (2020) documented a similar explanation. They argued that the Halloween effect could be explained by seasonal variations in investor mood. The authors found evidence that stocks that perform better (worse) in past periods when investors have a high (low) mood tend to also perform better (worse) in future periods when this high (low) mood is expected again. The authors hypothesize September and October to be low mood periods and March tend to be a high mood. This is consistent with the previous discussed findings. They argued that this might explain why there are higher returns in March (winter) and lower returns in September and October (summer).

Cao & Wei (2005) also linked an environmental variable to people's behavior. They first demonstrated that temperature can have a significant influence on mood, while mood in turn influences behavior. Psychological evidence shows that low temperatures lead to aggression, while high temperatures also lead to aggression, but hysteria and apathy as well. The authors then hypothesized that low temperatures lead to higher stock market returns, because investors behave more aggressive or risk-seeking. On the other hand, they also hypothesized that high temperatures lead to either higher returns as well, but can also lead to lower returns since apathy leads to more risk-averse behavior. The authors then showed that apathy dominates aggression when the temperature is high. Therefore, they found strong evidence of a temperature anomaly: a negative relationship between temperature and stock market returns. This could help explain the Halloween effect as well, as in winter months temperatures tend to be lower, which would lead to higher returns according to this framework. Jacobsen & Marquering (2008) also revisited this temperature link to stock market returns. Similar to the SAD anomaly, the authors argued that the suggested relation is likely to be one of correlation instead of causation. Jacobsen & Marquering (2009) even argued that any variable with a strong summer winter pattern can 'explain' the Halloween effect. This holds for SAD and temperature, but the authors showed that ice cream consumption and airline travel do the trick as well.

Carrazedo et al. (2016) argued that the Halloween effect may not be caused by changes in investor behavior as suggested by the previous argumentations. They found that the anomaly may be related to negative average returns during the summer rather than the significant positive average returns during the winter. The authors argue that the Halloween effect could be related to certain events, such as flows from mutual funds, that cause prices to constantly be negative during summer months.

Lloyd et al. (2017) argued that the Halloween effect may be caused by a self-fulfilling prophecy. Investors know that the Halloween effect exists and expect the market to deteriorate in May and increase again in November. That is why they liquidate their portfolios in May, which puts downward pressure on the market. These investors come back to the market in November, resulting in a higher demand for stocks, and thus higher price movements. This pattern is expected to happen year after year, resulting in a self-fulfilling prophecy.

2.5 Profit from the Halloween effect

If the Halloween effect is real, investors may profit from implementing Halloween effect-based investment strategies. Malkiel (2003) argued that seasonal anomalies don't appear to offer such arbitrage opportunities, as high transaction costs are involved to make use of them. Andrade et al. (2013) argued that most seasonal anomalies are indeed useless for investors. For example, 52 transactions are needed to exploit the Monday effect and even more, 252 trades a year, are needed to exploit the Day and Night effect. However, the Halloween effect is different. This anomaly only requires 2 trades per year. The authors argued that this is one reason why the Halloween effect is especially attractive for investors. Another reason is the relatively simple way of implementing the trading rule (Haggard & Witte, 2010), as an investor should simply buy a market portfolio in November and sell it at the start of May, and hold a risk-free asset in the summer period. This raises the question if and how profitable a Halloween strategy can be. Therefore, this section provides an overview of studies that claimed that it is possible to profit from Halloween effect-based investment strategies and studies that claimed otherwise.

Bouman & Jacobsen (2002) examined the profitability by comparing the annual returns of the Halloween strategy to the annual returns of a normal Buy and Hold strategy. The latter investment strategy tells investors to simply buy and hold the market portfolio throughout the whole year. It is a kind of benchmark. The authors found that a Halloween effect-based investment strategy outperforms the Buy and Hold strategy in 35 out of the 37 investigated countries. They also pointed out that the Halloween strategy has a substantially lower standard deviation in all countries. Zhang & Jacobsen (2021) investigated the same countries, but over a newer period, 1998 to 2017. They found that the

Halloween strategy is still profitable in 30 out of the 37 countries, while the standard deviations are again lower for all countries. Haggard & Witte (2010) also compared the Halloween strategy to the Buy and Hold strategy and found that even after the introduction of transaction costs of 1 percent per year, the Halloween strategy outperforms the Buy and Hold strategy. Swinkels & van Vliet (2012) tested the interaction of the five most famous calendar effects. They concluded that both the turn of the month effect and the Halloween effect are the strongest. They argued that investors are able to make higher risk-adjusted returns following investment strategies of these two anomalies. Andrade et al. (2013) introduced three market timing strategies to show that it is possible to exploit the Halloween effect. They denoted such a market timing strategy by (w_1;w_2). These weights represent the fraction of the total portfolio invested in the summer period, w_1, and winter period, w_2. The normal Buy and Hold strategy could be denoted as (1;1), whereas the market timing strategies are denoted as (0.75;1.25), (0.5;1.5) and (0;2). They concluded that the three latter strategies all outperformed the Buy and Hold strategy, in particular the most aggressive (0;2) timing strategy. Haggard et al. (2015) agreed that a Halloween strategy can outperform. However, they also stressed that outliers continue to play a role. If a series of years occur without outliers, the Halloween strategy may underperform. That is why the authors stressed that investors should always invest over a long-term horizon, so they are able to profit if significant outliers occur. Carrazedo et al. (2016) found that the Halloween strategy works in two out of every three calendar years. Maybe even more interesting is that the authors also found that the Halloween strategy outperforms the Buy and Hold strategy by 2.4 percent, while the risk on an annual basis is reduced by 7.5 percent. This implies more return and less risk: the dream of every investor. Lloyd et al. (2017) proposed an even more aggressive investment strategy called ‘’summer short’’. This new investment strategy also buys a market portfolio in the winter, just like the Halloween strategy. However, it suggests selling a market portfolio in the summer to exploit the relatively low summer returns instead of investing in a risk-free asset. They found that this new investment strategy outperforms the Halloween strategy by 3.20 percent and the Buy and Hold strategy by 4.77 percent.

All these results seem to indicate that investors are able to exploit the Halloween effect. However, there are also some studies that concluded something different. Dichtl & Drobetz (2014) showed that the Halloween strategy never outperformed a Buy and Hold strategy by implementing the Super Predictive Ability test or SPA-test of Hansen (2005). This is a test that compares a certain forecast procedure to an alternative forecast procedure, based on real-valued loss functions. A year later, Dichtl & Drobetz (2015) argued that most prior studies suffer from several shortcomings. For example, one shortcoming is that prior studies simply focused on all available data without checking whether adequate investment instruments are available during that time period to exploit the Halloween effect. According to them, another crucial issue is that most prior studies fail to take into account the publication date of the Halloween effect, as the findings may very well change after the anomaly has become publicly known. They concluded that investors should exploit the Halloween effect in the future with caution.

All the previously mentioned studies in this chapter examined the profitability of the Halloween effect on an index level. Arendas et al. (2018) is one of the few studies, if it is not the only study, that approached it differently. They studied whether profits can be made using a Halloween effect-based investment strategy on the individual stocks level. Investors may profit even more from investing in certain specific stocks that experience a strong Halloween effect instead of investing in a whole index. That's why the authors investigated the Dow Jones Industrial Average to see what can be concluded on the micro level. They found that there are huge differences between stocks. For example, Caterpillar and Walt Disney experienced the Halloween effect in most years, namely in 29 out of the 37 investigated years. On the other hand, Procter & Gamble only experienced the Halloween effect in 14 out of the 37 investigated years. Moreover, there are huge differences between the average winter and summer returns of these stocks. This shows that investors should also consider investing in individual stocks that experience a strong Halloween effect rather than only focusing on the major indices.

3. Research problem and hypotheses

This chapter provides the research problem and the research question. After that, the hypotheses are formulated.

3.1 Research problem

When reviewing the existing literature on the Halloween effect, almost all research analyzed the anomaly using stock indices. For example, Zhang & Jacobsen (2021) examined 114 stock indices for which data is available and confirmed that the Halloween effect is still remarkably robust all around the world. Although this is an interesting result on the macro level, this paper tries to shed even more light on the Halloween effect by considering the micro level. To be more specific, individual stocks that are included in an index are investigated to see how the Halloween effect is determined. There is one previous study that has conducted research on this micro level. Arendas et al. (2018) investigated the individual stocks of the Dow Jones Industrial Average and found that some stocks experienced a very significant Halloween effect, while others did not. This indicates that it may be worthwhile for investors to change their investment behavior by also focusing on individual stocks following the Halloween strategy. The authors concluded that this could be the case for other indices as well, but that further research is necessary to confirm this. That’s why this paper looks at the German DAX 30 to fill this gap in research. Today, the DAX is one of the most important stock indices worldwide. For example, it serves as an underlying for more than 150,000 financial products and its futures contracts are considered among the five most popular ones globally[7]. Therefore, the research question is formulated as follows:

***Research question**: ’’Do the individual stocks of the DAX 30 experience a significant Halloween effect?’’*

This paper goes one step further as additionally, several stock characteristics (beta, size and book-to-market value) are investigated to further see where the anomaly is concentrated. Again, the results could change the investment strategy of investors if it turns out that it is more profitable to invest in stocks with certain specific characteristics following a Halloween strategy.

3.2 Hypotheses

This purpose of this paper is to take a closer look at the Halloween effect in Germany. To do so, it is first interesting to see whether the Halloween effect is present in the whole index, the DAX, over the period 1988-2020. Various previous studies have confirmed the existence of the Halloween effect in Germany over different time periods (e.g. Bouman & Jacobsen, 2002; Andrade et al., 2013; Zhang & Jacobsen, 2021). Therefore, the first hypothesis is formulated as follows:

[7] https://deutsche-boerse.com/dbg-en/our-company/30-facts-about-30-years-of-DAX-29994

Hypothesis 1*: The Halloween effect is present in the DAX over the period 1988 to 2020*

The result of this hypothesis shows whether the Halloween effect exists in the index. It is also important to test for the influence of the January effect on the Halloween effect (Bouman & Jacobsen, 2002; Jacobsen & Visaltanachoti, 2009; Zhang & Jacobsen, 2021). This is a different anomaly that states that returns are higher in January than in the other months of the year. Several authors argued that the January effect has nothing to do with the Halloween effect (e.g. Bouman & Jacobsen, 2002; Haggard & Witte, 2010; Carrazedo et al., 2016), while Lucey & Zhao (2008) argued that the Halloween effect is not independent of the January effect. Therefore, the second hypothesis is formulated as follows:

Hypothesis 2*: The Halloween effect is present in the DAX once corrected for the January effect over the period 1988 to 2020*

After these two hypotheses, this paper takes a closer look at the Halloween effect in Germany. Individual stocks that satisfy the three conditions described in Chapter 4.1 are analyzed to determine which stocks experience the Halloween effect. It is interesting to look at this micro level, because there is a possibility that only several companies drive the Halloween effect. This is important information for investors, because this would imply that they can make more profit if they invest in certain stocks rather than in the index. Arendas et al. (2018) investigated individual stocks of the Dow Jones and concluded that it is not likely that the Halloween effect is driven by a handful of companies. Moreover, they found that the majority of the individual companies experienced the Halloween effect. Although they assumed that this could be valid for other indices as well, they pointed out that further research is necessary to corroborate this assumption. Therefore, following Arendas et al. (2018), hypothesis 3 is formulated as follows:

Hypothesis 3*: The Halloween effect is present in more than half of the individual stocks of the DAX*

The result of this hypothesis shows whether the Halloween effect is present in individual stocks. However, it is also important to investigate how many of the analyzed stocks experience a significant Halloween effect, especially for investors. Arendas et al. (2018) found that in the case of the Dow Jones 18 of the 35 analyzed stocks showed a significant Halloween effect at a p-value of 0.1. Therefore, again following Arendas et al. (2018), hypothesis 4 is formulated as follows:

Hypothesis 4*: The Halloween effect is significant in more than half of the individual stocks of the DAX*

After this analysis, different stock characteristics are investigated to see whether the Halloween effect is concentrated in specific stocks. It is possible that the Halloween effect is concentrated in firms with a high or low value of a certain stock characteristic. This would shed a different light on the Halloween effect. The first stock characteristic that will be investigated is the beta. According to the capital asset pricing model (CAPM), first documented by Sharpe (1964) and Lintner (1965), high beta stocks should earn higher returns to compensate investors for bearing a higher risk. Therefore, it could be that the Halloween effect is mostly present in high beta companies within an index. Fiore & Saha (2015) demonstrated that the relationship between the beta and returns is different between summer and winter months in the U.S. They showed that high beta stocks do indeed earn higher returns than low beta stocks in the winter as predicted by CAPM, but low beta stocks outperformed high beta stocks during the summer. Jacobsen & Visaltanachoti (2009) considered the beta in different U.S. sectors and found that low beta sectors seem to have a lower Halloween effect than high beta sectors, although it is not entirely clear. Therefore, the fifth hypothesis is formulated as follows:

Hypothesis 5*: The Halloween effect is more present in high beta stocks than in low beta stocks*

The second stock characteristic that will be investigated is the size. Instead of only using the market return, Fama & French (1992) added two more factors to CAPM: a size factor and a value factor (book-to-market ratio) to capture the variation in average stock returns. The size factor mimics the risk factor in returns related to size. They found that smaller firms have higher average returns. Therefore, it could be that the Halloween effect is mostly present in the smaller companies within an index. Dzhabarov & Ziemba (2010) investigated the difference between large-cap stocks (S&P 500 stock index) and small-cap stocks (Russell 2000 stock index). They found that the Halloween effect was stronger for small-cap stocks. On the other hand, Jacobsen et al. (2005) showed that the Halloween effect is not related to size. Therefore, the sixth hypothesis is formulated as follows:

Hypothesis 6*: The Halloween effect is more present in small stocks than in large stocks*

The third stock characteristic that will be investigated is the book-to-market ratio. Fama & French (1992) found that firms with a high book-to-market value have higher average returns than firms with a low book-to-market ratio. Therefore, it could be that the Halloween effect is mostly present in high book-to-market ratio companies within an index. O'Brien et al. (2010) looked at the Australian stock market and also found this positive relationship between book-to-market ratio and average returns. However, according to Jacobsen et al. (2005) the book-to-market ratio does not affect the Halloween effect. Therefore, the seventh hypothesis is formulated as follows:

***Hypothesis** 7: The Halloween effect is more present in high book-to-market ratio stocks than in low book-to-market ratio stocks*

4. Data and research methodology

This chapter provides the data and research method used to test the different hypotheses formulated in Chapter 3.

4.1 Data

To answer the formulated research question, a quantitative research method will be used. First of all, data from the German stock market index, the DAX 30, will be retrieved from Thomson Reuters Eikon over the period November 1988 to November 2020. Following Carrazedo et al. (2016), the same start month and end month is taken to allow for an equal number of observations in both the winter period and the summer period. To be more specific, monthly returns of the DAX 30 are taken from Eikon. This data is needed for hypothesis 1 and hypothesis 2.

In order to test whether the Halloween effect is present and significant in individual stocks (hypothesis 3 and hypothesis 4), also data of individual stocks of the DAX are retrieved from Thomson Reuters Eikon. It is impossible to include all the companies of the DAX in the analysis, as some companies go bankrupt or are acquired by other companies. Therefore, stocks that are analyzed must satisfy the following three conditions: (1) it was included in the DAX 30 for some time during the period 1988-2020, (2) the original company still exists and the shares of the company are publicly traded and (3) price data for at least 20 years since 1988 is available. These conditions are based on the study of Arendas et al. (2018).

The selection shows that 56 different companies have been included in the DAX since 1988 (condition 1). Some of these companies were acquired by another company or went bankrupt. The selection shows that 44 companies still exist and are publicly traded (condition 2). However, for some of these companies price data is not available for at least 20 years. The selection shows that for 33 companies there is enough price data available (condition 3). These companies are presented in Table 8 of Appendix A. A detailed list of all the companies that have been included in the DAX during the period 1988 to 2020 for some time along with information about which conditions they failed to meet can be found in Table 9 of Appendix A.

In order to test whether the Halloween effect is more present in certain specific stocks, data on the different stock characteristics (beta, size and book-to-market ratio) are also retrieved from the different individual companies. This data is needed to test hypothesis 5,6, and 7.

4.2 Research methodology

To test *hypothesis 1*, this paper investigates whether the winter returns are significantly higher than the summer returns in the DAX 30. Following mainstream research (e.g. Bouman & Jacobsen, 2002; Andrade et al., 2013, Carrazedo et al., 2016), this is done using the following OLS regression:

$$R_t = \beta_0 + \beta_1 S_t + \varepsilon_t$$

where R_t represents the return of the stock market in month t, β_0 represents the average monthly return over the time period May to October, S_t is a seasonal dummy variable that takes the value of '1' in the winter months and '0' otherwise, ε_t is the error term and β_1 indicates the size and statistical significance of the Halloween effect.

To test *hypothesis 2*, this paper investigates what the influence of the January effect is on the Halloween effect. As discussed in Chapter 3, it is important to test for this influence as it may change the results. Therefore, the second regression model includes a January dummy to correct for this potential effect:

$$R_t = \beta_0 + \beta_1 S_t^{adj} + \beta_2 Jan_t + \varepsilon_t$$

where Jan_t represents the January dummy that takes the value of '1' in January and a value '0' in all the other months, S_t^{adj} is the adjusted seasonal dummy that takes the value of '1' during November to April, January excluded, and a value of '0' otherwise and β_2 shows the coefficient of the January effect.

To test *hypothesis 3*, this paper takes a closer look at the Halloween effect. The individual stocks of the DAX 30 will be investigated. To test whether an individual stock followed the Halloween effect pattern, the percentage of higher average winter returns than average summer returns, the percentage of Halloween effect years, are calculated. As this requires data about years instead of monthly data, a new data set is generated with yearly data. Therefore, the original data is collapsed to calculate the average winter return and average summer return per firm per year. Ultimately, another dummy is created that has value 1 if the particular firm has a higher winter return in that particular year, and a value 0 if the particular firm has a higher summer return in that particular year. The percentage of Halloween effect years must be at least higher than 50 for it to be possible that the particular stock is affected by the Halloween effect, as there are only two outcomes when investigating the Halloween effect. Because there is simply a 50% chance that the average winter returns are higher than the average summer returns, a binomial test is conducted to see if the observed results differ from what is expected, as it is possible that the results are only a matter of chance.

To test *hypothesis 4*, the parametric two-sample t-test and the non-parametric Wilcoxon rank-sum test are used. A Shapiro-Wilk test is performed to determine whether the individual data series are normal distributed or non-normal distributed, and thus whether it is better to use the two-sample t-test or Wilcoxon rank-sum test. If the data is normally distributed, the two-sample t-test is the better choice.

To test *hypothesis 5 to 7*, the sample of the individual stocks is divided in two deciles based on the average of each different stock characteristic. These two deciles consist of high beta stocks and low beta stocks, small cap stocks and large cap stocks and high book-to-market ratio stock and low book-to-market ratio stocks. To test whether the Halloween effect occurs in the different deciles, OLS regressions are performed. These regressions are performed separately for the different high and low deciles. If there is a difference in the significance level of the high decile coefficient and low decile coefficient, it suffices to continue using this regression. This is because it is possible to argue that one decile experiences a stronger Halloween effect than the other decile, as the p-values differ between the two deciles. This also holds if the results are not significant. However, it is not possible to argue that one decile experiences a stronger Halloween effect than the other if the p-values of the high decile coefficient and low decile coefficient are equal[8]. If that is the case, another OLS regression is performed with an interaction term to test whether one decile experiences a stronger Halloween effect than the other. Instead of two separate regressions, this is one regression in which the stock characteristic itself is also included. The regression model looks as follow:

$$P_t = \beta_0 + \beta_1 W_t + \beta_2 SC_t + \beta_3 W_t SC_t + \varepsilon_t$$

where W_t represents the Halloween effect, SC is a dummy that represents the particular stock characteristic that takes the value of '1' in the higher decile and '0' in the lower decile, and $W_t SC$ represents the interaction between the two.

To test *hypothesis 5*, the monthly beta of each analyzed firm is calculated in Thomson Reuters Eikon using the following formula:

$$\beta_i = \frac{cov(r_i, r_p)}{var(r_p)}$$

where β_i represents the beta of firm i, $cov(r_i, r_p)$ represents the covariance between r_i and r_p, $var(r_p)$ represents the variance of r_p, r_i represents the return of firm i and r_p is the return of the DAX.

To test *hypothesis 6*, the market capitalization is retrieved from Thomson Reuters Eikon. This is used as a measure of size following for example Fama & French (1992).

To test *hypothesis 7,* monthly book-to-market ratios are required. As Thomson Reuters Eikon only provides market-to-book ratios, the monthly book-to-market ratios are calculated as follows:

$$book - to - market\ ratio = \frac{1}{market - to - book\ ratio}$$

[8] For more information regarding this statistical issue, see Chapter 5.3.

5. Results

This chapter provides the results of this paper. First, the DAX is investigated as an index. After that, the individual companies of the DAX are examined. Finally, different stock characteristics are investigated to further determine in what stocks the Halloween effect is concentrated.

5.1 Halloween effect and the DAX 30

The main goal of this paper is to take a closer look at the Halloween effect in Germany. However, first, this paper takes a step back and examines the DAX 30. Figure 1 provides the average returns of the DAX over the period November 1988 to November 2020. Eyeballing the data already gives the feeling that the Halloween effect is present in Germany, as the three highest mean returns per month can all be found in the winter[9]. The figure also indicates that the January effect may not influence the Halloween effect that much, as the average return is only slightly more than 1 percent.

FIGURE 1: AVERAGE MONTHLY RETURN DAX 30

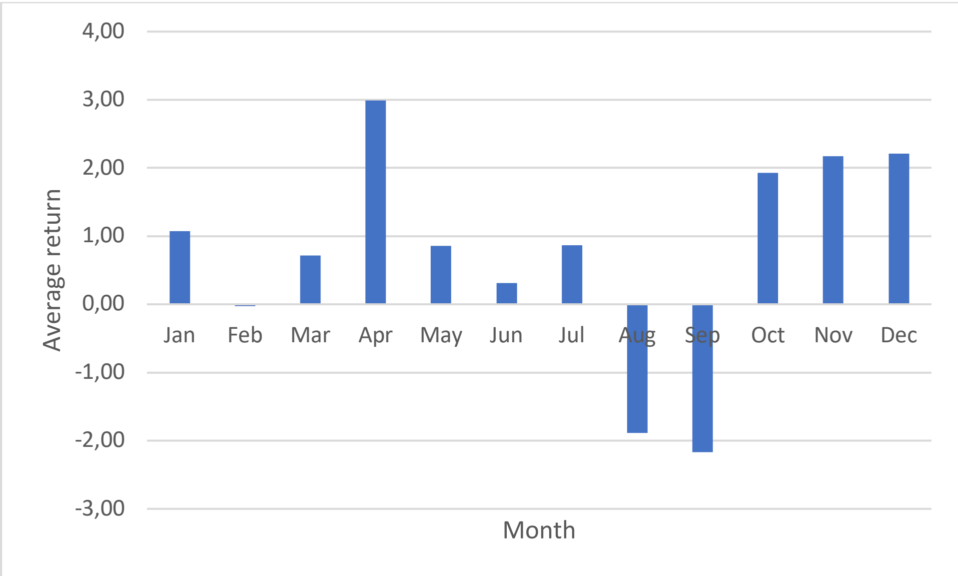

Figure 1 presents the average monthly returns of the DAX 30 over the period November 1988 to November 2020.

To formally test these presumptions and thereby also the first and second hypothesis, Table 1 provides the results of both regression models, with and without a January dummy. The results show that the Halloween effect is statistically significant in Germany over the time period November 1988 to November 2020 (see Sample Period I). Also, the results show that the January effect is not related to the Halloween effect in Germany. The t-value is even slightly higher for the regression model with the January dummy (see Regression Model II). This means that the Halloween effect is stronger once corrected for the January effect. Therefore, this paper confirms prior studies that argued that the January effect does not influence the Halloween effect (e.g. Haggard & Witte, 2010; Carrazedo et al., 2016). However, it is not possible to say that there is no January effect in Germany. Bouman & Jacobsen (2002)

[9] The three highest average returns are all recorded in the winter: April with 2.99%, followed by December, 2.21%, and November, 2.17%

also included a January dummy in their analysis and argued that the inclusion of this dummy may overstate the January effect and understate the Halloween effect, as all excess returns in January are now because of the January effect. Nevertheless, the numbers do not indicate the presence of the January effect in Germany over Sample Period I.

Table 1 shows that Sample Period I is divided into two smaller sample periods to determine how robust the Halloween effect is. These sample periods run from November 1988 to November 2004, called Sample Period II, and from November 2004 to November 2020, called Sample Period III. This is not only a robustness check, but it also helps reducing the problem of data mining. Schwert (2003) proposed that the analysis of newly available data is one solution to this problem. The results show that the Halloween effect is present over Sample Period II, even after correcting for the possible January effect. However, the results also show that the Halloween effect is not significant anymore over the latest Sample Period III. Nevertheless, the estimated coefficients are still in the expected direction, which means that winter returns are higher than summer returns, and thus the Halloween effect is present.

TABLE 1: OLS REGRESSION

Stock index	Regression model I		Regression model II (with January dummy)		
	β_0 t-value/p-value	β_1 t-value/p-value	β_0 t-value/p-value	β_1 t-value/p-value	β_2 t-value/p-value
Sample Period I: November 1988 to November 2020					
DAX	-0,02	1,54**	-0,02	1,63***	-0,53
	-0,04 / 0,970	2,55 / 0,011	-0,04 / 0,970	2,57 / 0,010	-0,47 / 0,641
Sample Period II: November 1988 to November 2004					
DAX	-0,35	2,28**	-0,35	2,18**	0,55
	-0,55 / 0,580	2,53 / 0,012	-0,55 / 0,581	2,31 / 0,022	0,32 / 0,746
Sample Period III: November 2004 to November 2020					
DAX	0,32	0,80	0,32	1,07	-1,62
	0,56 / 0,574	1,00 / 0,320	0,56 / 0,574	1,27 / 0,205	-1,06 / 0,289

Table 1 presents the regression results of both OLS regressions as described in Chapter 4.2. Regression model I is the regression without a January dummy and regression model II is the regression with a January dummy. Three different time periods are used that are labeled as Sample Period I, II and III. β_0 represents the average monthly return over the time period May to October, β_1 represents the average monthly return over the period November to April and thus indicates the size and statistical significance of the Halloween effect and β_2 represents the coefficient of the January effect. The values of these estimated coefficients are on top in the box, the t-value and p-value are below. * = statistically significant at a p-value of 0.1; ** = statistically significant at a p-value of 0.05; *** = statistically significant at a p-value of 0.01. The estimated coefficients have been rounded to two decimals.

One potential reason that the results over Sample Period III are not significant could be the global financial crises that started in 2007. This crisis caused a recession in the eurozone in the first quarter of 2008. Just like other countries, Germany was hit hard. The GDP of Germany fell by a total of 6.6 percentage points in 2008 and the first quarter of 2009. The German economy recovered in the following years. In the first quarter of 2011, the GDP level was already back at the level of before the crisis (Storm & Naastepad, 2015). To really determine whether the global financial crisis indeed affected the

Halloween effect, the time period 1988 to 2020 is divided into three subperiods. These subperiods consist of one pre-crisis period, called Sample Period IV, one crisis period, called Sample Period V and one post-crisis period, called Sample Period VI (see Table 2). Consistent with the GDP numbers in Germany, the crisis period is taken from November 2007 to November 2010. Again, a regression analysis with and without a January dummy is performed.

The results show that the Halloween effect is statistically significant in Germany during the pre-crisis period, also after correcting for the January effect. During the crisis period, the Halloween effect is not statistically significant. One remarkable finding is that the estimated coefficient of the January effect during this period is statistically significant, but not in the direction that is expected. A closer look at the data reveals that this period includes three very negative January returns, causes the estimated coefficient to be extremely negative and the p-value to be significant. During the post-crisis period, the Halloween effect is also not statistically significant in both regression models. One potential reason could be that it takes some more time for investors to go back to their pre-crisis behavior. Nevertheless, the estimated coefficients are again in the expected direction.

Although the Halloween effect seems to weaken in strength after the financial crisis of 2008 in Germany, it is still highly significant over the whole time period (see Sample Period I). Therefore, Hypothesis 1 can be accepted, suggesting that the Halloween effect is present in Germany. The numbers also show that the January effect is not related to the Halloween effect. Therefore, Hypothesis 2 can also be accepted, suggesting that the Halloween effect is present in the DAX once corrected for the January effect.

TABLE 2: OLS REGRESSION AND THE FINANCIAL CRISIS

Stock index	Regression model I		Regression model II (with January dummy)		
	β_0 t-value/p-value	β_1 t-value/p-value	β_0 t-value/p-value	β_1 t-value/p-value	β_2 t-value/p-value
Sample Period IV: November 1988 to November 2007					
DAX	0,05 -0,10 / 0,923	2,05*** 2,62 / 0,009	-0,05 -0,10 / 0,923	1,95** 2,38 / 0,018	0,56 0,38 / 0,705
Sample Period V: November 2007 to November 2010					
DAX	-0,49 -0,27 / 0,788	0,57 0,22 / 0,825	-0,49 -0,30 / 0,770	2,58 1,05 / 0,303	-12,06** -2,70 / 0,011
Sample Period VI: November 2010 to November 2020					
DAX	0,20 0,29 / 0,774	0,86 0,88 / 0,378	0,20 0,29 / 0,774	0,72 0,70 / 0,483	0,84 0,45 / 0,651

Table 2 presents the regression results of both OLS regressions as described in Chapter 4.2. Regression model I is the regression without a January dummy and regression model II is the regression with a January dummy. Three different time periods are used that are labeled as Sample Period IV, V and VI. β_0 represents the average monthly return over the time period May to October, β_1 represents the average monthly return over the period November to April and thus indicates the size and statistical significance of the Halloween effect and β_2 represents the coefficient of the January effect. The values of these estimated coefficients are on top in the box. * = statistically significant at a p-value of 0.1; ** = statistically significant at a p-value of 0.05; *** = statistically significant at a p-value of 0.01. The estimated coefficients have been rounded to two decimals.

5.2 Halloween effect and the individual stocks of the DAX 30

This paper now takes a closer look at the DAX. The analyzed companies that satisfy the conditions are presented in Table 3 along with information about the presence of the Halloween effect. One thing that immediately strikes is that almost all analyzed companies, 32 of the 33, experienced the Halloween effect in more than 50% of the investigated years. The two companies that are most heavily affected in this regard are Adidas and MAN. The famous sportswear company experienced the Halloween effect in 20 of the 25 years, 80,00% of the cases, whereas the manufacturing company MAN experienced the Halloween effect in 28 of the 32 years, 87,50% of the cases. Besides these two, almost all companies experienced the Halloween effect in 50% to 80% of the cases. The only exception is Munich Re. The reinsurance company experienced the Halloween effect in 15 of the 32 years, which equals 46,88%. The last row of Table 3 shows that the DAX 30 experienced the Halloween effect in 23 of the 32 years, 71,88% of the cases. The table reveals that 9 of the 33 analyzed companies experienced a higher percentage of Halloween effect years than the DAX.

Table 3 also shows the average winter returns, average summer returns and the difference between the two. All 33 analyzed companies show a positive number for the difference between the winter period and the summer period. This means that there is no single company that performed better during the summer compared to the winter. The average winter returns seem to be the driver behind this, as all analyzed companies recorded positive average winter returns. However, as can be seen in the table, it also helps that there are a lot of companies that experienced negative average summer returns. The three companies with the highest average winter returns, 2,63%, are chemical company K+S, MAN and software company SAP. The company with the lowest average winter return, 0,63%, is energy company RWE. However, even this company has a higher average winter return than average summer return, as the latter shows a value of 0,59%, keeping the difference between the two still positive.

Based on the abovementioned results, Hypothesis 3 can be accepted, suggesting that the Halloween effect is present in more than half of the individual stocks of the DAX.

TABLE 3: THE PRESENCE OF THE HALLOWEEN EFFECT

Firm	Percentage of Halloween effect years	Average Winter returns (W)	Average Summer returns (S)	Difference W-S in percentage
Adidas	80,00	2,51%	0,35%	2,16
Allianz	65,62	1,39%	-0,09%	1,30
BASF	78,12	2,01%	-0,51%	1,50
Bayer	71,88	1,41%	-0,25%	1,16
Beiersdorf	71,88	1,54%	0,43%	1,11
BMW	65,62	1,78%	0,03%	1,75
Commerzbank	65,62	0,95%	-1,04%	1,99
Continental	68,75	1,91%	0,16%	1,75
Daimler	63,64	0,88%	-0,24%	1,12
Deutsche Bank	59,38	1,34%	-0,82%	2,16
Deutsche Lufthansa	62,50	1,48%	-0,53%	2,01
Deutsche Telekom	50,00	0,91%	-0,37%	1,28
E.ON SE	56,25	1,16%	-0,23%	1,39
Fresenius	64,29	2,43%	0,45%	1,98

Fresenius Medical Care	75,00	1,62%	-0,18%	1,80
Hannover RE	65,38	1,73%	0,47%	1,26
HeidelBergCement	78,12	1,54%	-0,08%	1,62
Henkel	65,62	1,35%	0,29%	1,06
Infineon Technologies	61,90	2,23%	-0,10%	2,33
K+S	75,00	2,63%	-0,97%	3,60
Linde plc	60,71	1,92%	0,60%	1,32
MAN	87,50	2,63%	-1,08%	3,71
Merck	60,00	1,38%	0,66%	0,72
MLP	60,00	2,44%	-0,28%	2,72
Munich Re	46,88	0,88%	0,84%	0,04
ProSiebenSat.1 Media	69,57	2,58%	0,33%	2,25
TUI	75,00	1,94%	-0,94%	1,00
RWE	56,25	0,63%	0,59%	0,04
Salzgitter	68,75	1,91%	-0,49%	2,40
SAP	59,38	2,63%	1,30%	1,33
Siemens	56,25	1,65%	0,15%	1,50
ThyssenKrupp	65,62	1,42%	-0,68%	2,10
Volkswagen Group	56,25	1,45%	0,80%	0,65
DAX 30	71,88	1,52%	-0,02%	1,54

Table 3 presents the presence of the Halloween effect of the analyzed companies. The time period differs between companies. This can be found in Table 8 of Appendix A. The DAX 30 is also added to this list of stocks to make the comparison easier between the DAX and the individual companies. The time period for the DAX is 1988 to 2020. The table is based on the work of Arendas et al. (2018).

Table 4 presents the statistical significance tests. First of all, the binomial test shows for how many of the analyzed companies the presence of the Halloween effect is more frequent than expected by chance. The results reveal that this is true for 8 of the 33 analyzed companies at a p-value of 0.01, for 12 companies at a p-value of 0.05 and for the majority, 20 companies, at a p-value of 0.1.

Although this is interesting, it may be even more interesting to consider the statistical significance of the different individual companies, especially for investors following Halloween effect-based investment strategies. Therefore, Table 4 also shows the results of the two sample t-test and Wilcoxon rank sum test. If the numbers are underlined, it means that this test is the most appropriate test of the two based on whether the data series is normally distributed or not. The results reveal that 4 of the 33 companies record a statistically significant Halloween effect at a p-value of 0.01, for 11 companies at a p-value of 0.05 and for 24 companies at a p-value of 0.1. This is an interesting result, as the DAX records a p-value of 0.011 over the period 1988 to 2020. This means that only 4 of the 33 companies show a more significant Halloween effect than the DAX, which are BASF, K+S, MAN and TUI. From this information, it seems possible to conclude that the significance of the DAX is driven by only a handful of companies. However, it is also important to note that not all companies that were once part of the DAX since 1988 have been included in the analysis. Therefore, it could be that there are more companies that drive the Halloween effect in Germany.

Based on the abovementioned results, Hypothesis 4 cannot be accepted, suggesting that the Halloween effect is not significant in more than half of the individual stocks of the DAX.

TABLE 4: STATISTICAL SIGNIFICANCE TESTS

Firm	Binomial test (p-value)	Two sample t-test (p-value)	Wilcoxon rank sum test (p-value)
Adidas	0,0020***	0,0111**	0,0141**
Allianz	0,0551*	0,0787*	0,0741*
BASF	0,0011***	0,0003***	0,0002***
Bayer	0,0100***	0,0297**	0,0881*
Beiersdorf	0,0100***	0,0726*	0,0328**
BMW	0,0551*	0,0266**	0,0291**
Commerzbank	0,0551*	0,1021	0,0986*
Continental	0,0251**	0,1018	0,0566*
Daimler	0,1431	0,3514	0,3981
Deutsche Bank	0,1886	0,0161**	0,0413**
Deutsche Lufthansa	0,1077	0,0529*	0,0399**
Deutsche Telekom	0,5806	0,1684	0,4455
E.ON SE	0,2983	0,0293**	0,0639*
Fresenius	0,0925*	0,0520*	0,0713*
Fresenius Medical Care	0,0113**	0,0386**	0,0578*
Hannover RE	0,0843*	0,1975	0,2201
HeidelBergCement	0,0011***	0,0916*	0,0286**
Henkel	0,0551*	0,0758*	0,0763*
Infineon Technologies	0,1917	0,1160	0,1218
K+S	0,0035***	0,0003***	0,0001***
Linde plc	0,1725	0,0182**	0,0738*
MAN	0,0000***	0,0004***	0,0006***
Merck	0,2122	0,3246	0,3467
MLP	0,1808	0,0362**	0,0669*
Munich Re	0,7017	0,9549	0,5820
ProSiebenSat.1 Media	0,0466**	0,3712	0,2970
TUI	0,0035***	0,0124**	0,0031***
RWE	0,2983	0,9586	0,6480
Salzgitter	0,0251**	0,0286**	0,0145**
SAP	0,1885	0,1422	0,2427
Siemens	0,0551*	0,0525*	0,0678*
ThyssenKrupp	0,0551*	0,0419**	0,0387**
Volkswagen Group	0,2983	0,5705	0,5106

Table 4 presents the statistical significance tests of the analyzed companies. * = statistically significant at a p-value of 0.1; ** = statistically significant at a p-value of 0.05; *** = statistically significant at a p-value of 0.01. The table is based on the work of Arendas et al. (2018).

5.3 Halloween effect and stock characteristics

This paper now digs even deeper into the Halloween effect. Different stock characteristics are investigated to get a better understanding of how the Halloween effect is determined. First, OLS regressions are performed on two deciles, high beta versus low beta companies, high book-to-market ratio versus low book-to-market ratio companies and large versus small companies. The results of these regressions are presented in Appendix D, E and F. The results in Appendix D show that the coefficient for the Halloween effect is somewhat stronger for high beta companies, 1.838, in comparison to low beta companies, 1.669. They are both statistically significant with a p-value of 0.000. However, this does not mean that it is possible to argue that high beta companies experience a stronger Halloween effect than low beta companies. This might be expected if you simply look at the coefficients. Such an argumentation is only possible if high beta companies are also significantly stronger. This is not the case. As there are no significance values for the difference in strength of the coefficients, another OLS regression is performed with an interaction term to account for this statistical issue. Instead of two separate regressions, this is one regression model in which the stock characteristic itself is also included[10]. The results are presented in Table 5, Table 6 and Table 7. Table 5 shows a significant Halloween effect (winter) with a β = 1.669. For the high beta companies, this coefficient increases with 0.169. This means that high beta companies experience the Halloween effect somewhat more than low beta companies. With this regression, it also possible to observe whether this difference is statistically significant. This is not the case (β = 0.169, not significant). Therefore, Hypothesis 6 cannot be accepted, suggesting that the Halloween effect is not more present in high beta stocks than low beta stocks.

TABLE 5: OLS REGRESSION STOCK CHARACTERISTIC BETA

	(1)
VARIABLES	price
winter	1.669***
	(0.251)
beta01	-0.206
	(0.253)
winter#beta01	0.169
	(0.358)
Constant	0.0463
	(0.177)
Observations	11,762
R-squared	0.008

Table 5 presents the OLS regression of the stock characteristic beta with interaction term. The variable beta01 represents the beta itself. This means that the variable itself is also included in the model. As it is included, the beta explains something with regard to prices (see footnote 10). This is the reason why the coefficients are slightly different between this model and the model presented in Appendix D. Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

The next stock characteristic is the size. The results show, again, a statistically significant Halloween effect. However, even more interesting is that the interaction term between winter and size is statistically significant at a p-value of 0.1. This means that the Halloween effect is significantly stronger for small stocks than for large stocks ((β = -0.686, p-value < 0.1). This is what is expected. Therefore, Hypothesis 7 can be accepted, suggesting that the Halloween effect is more present in small stocks than in large stocks (at a p-value of 0.1).

[10] In the regression model with interaction term, the stock characteristic itself is also included, which are beta01, size01 and BTM01. For example, Table 5 shows that the coefficient of beta01 has a value of -0.206. This means that if a stock belongs to the higher decile, the price is lower compared to if a stock belongs to the lower decile. Beta01, size01 and BTM01 are kind of extra dummy variables that are included in the model to be able to test the Halloween effect in one regression. Because of that, this regression model is more comprehensive than the separate regressions that can be found in Appendix D, E and F.

TABLE 6: OLS REGRESSION STOCK CHARACTERISTIC SIZE

VARIABLES	(1) price
winter	2.082***
	(0.249)
size01	0.382
	(0.253)
winter#size01	-0.686*
	(0.358)
Constant	-0.239
	(0.176)
Observations	11,762
R-squared	0.008

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

The last stock characteristic is the book-to-market ratio. For the third time, the results show a statistically significant Halloween effect with a coefficient of 1.585. For the high book-to-market ratio companies, this coefficient increases with 0.337. This means that high book-to-market ratio companies experience the Halloween effect somewhat more than low book-to-market companies. This is what is expected. However, this difference is not statistically significant (β = 0.337, not significant). Therefore, Hypothesis 7 cannot be accepted, suggesting that the Halloween effect is not more present in high book-to-market ratio companies than low book-to-market ratio companies.

TABLE 7: OLS REGRESSION STOCK CHARACTERISTIC BOOK-TO-MARKET RATIO

VARIABLES	(1) price
winter	1.585***
	(0.252)
BTM01	-0.455*
	(0.253)
winter#BTM01	0.337
	(0.358)
Constant	0.170
	(0.178)
Observations	11,762
R-squared	0.008

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

6. Conclusion

This chapter provides the conclusion and discussion of this paper. Also, suggestions for further research are discussed.

6.1 Conclusion and discussion

Over the past two decades, a huge body of research has been dedicated to the 'Sell-in-May' anomaly, also known as the Halloween effect. The Halloween effect is the tendency that stocks perform better between November 1 and April 30 than in the other months of the year. Existing research investigates the effect primarily using stock indices. That's why this study digs a little bit deeper into the Halloween effect by considering the individual stocks level. To be more specific, individual stocks of the German DAX 30 are investigated to see how the Halloween effect is determined. Additionally, three different stock characteristics (beta, size and book-to-market value) are investigated to further see where the anomaly is concentrated. Therefore, seven different hypotheses were developed to determine how the Halloween effect looks like on the macro level and the micro level.

The results of the first analysis show that the Halloween effect is statistically significant in Germany over the period 1988 to 2020. This also holds after correction for the January effect. In some time periods, the month January even has a negative effect on the Halloween effect. The drivers behind the Halloween effect in Germany are the months April, November and December. The month April has the highest average return. This means that there is more like an 'April effect' than a January effect in Germany. It is important to note that the Halloween effect seems to weaken a bit since the financial crisis in 2008. One possible explanation is that it takes some more time for investors to go back to their pre-crisis behavior. It could also be that markets become more efficient and therefore, the Halloween effect seems to weaken over the last decade. This would be in line with Schwert (2003) and Malkiel (2003). They argued that anomalies tend to disappear after they have received considerable attention. Although this could be true, recent studies, such as Zhang & Jacobsen (2021), show no sign of a weakening Halloween effect. Moreover, the estimated coefficients in the crisis period and post-crisis period are in the expected direction which means that the Halloween effect pattern is still there, although not statistically significant.

The results of the second analysis give more insight into the Halloween effect in Germany. An analysis has been made on all the companies that have been included in the DAX since 1988. 33 different companies satisfied the criteria and an analysis has been made on these companies. The results reveal that for 32 of the 33 analyzed companies the Halloween effect is present in more than 50% of the investigated years. To put this in perspective, Arendas et al. (2018) investigated the Dow Jones in a similar way and found that the Halloween effect is present in 28 of the 35 analyzed companies. Moreover, although the numbers vary from stock to stock, all analyzed companies experienced higher average winter returns than summer returns. This shows how widespread the Halloween effect is in Germany. Probably the most interesting result of this paper is that only 4 companies record a statistically significant Halloween effect at a p-value of 0.01, while the DAX 30 itself records a p-value of 0.011. This means that only 4 of the 33 companies show a more significant Halloween effect than the DAX itself. This could imply that the Halloween effect is driven by only a handful of companies in Germany. As not all companies have been analyzed that were once included in the DAX, it is important to recognize that there may be other drivers of the Halloween effect in Germany. However, these companies were not analyzed for a reason. Either price data was not available for at least 20 years or the original company ceased to exist. This means that it is likely that these companies don't have a huge influence on the Halloween effect in Germany, as most of the non-analyzed companies were only part of the DAX for a short period of time because of the just mentioned reasons.

The results of the third analysis show that the Halloween effect is not related to the book-to-market ratio and not to the beta. This is line with Jacobsen et al. (2005) and Jacobsen & Visaltanachoti (2009). However, the Halloween effect is related to size, as the results show that smaller stocks tend to experience a more significant Halloween effect than larger stocks. This is not in line with Jacobsen et al. (2005), but is in line with Dzhabarov & Ziemba (2010). This result could mean that the stocks of the MDAX and SDAX, the mid-cap and small-cap indices of Germany, are even more heavily affected by the Halloween effect than the large-cap DAX. Further micro level research is necessary to investigate whether size is related to the Halloween effect in other indices as well.

Everything considered, the findings of this paper accelerate the need to take a closer look at other stock indices as well. The work of Arendas et al. (2018) and this paper strengthens the view that it may be even more profitable to invest in highly significant stocks that follow the Halloween effect pattern in comparison to a stock index itself. Many authors in the past (e.g. Bouman & Jacobsen, 2002; Haggard & Witte, 2010; Lloyd et al., 2017) have suggested that investors can make profits following the Halloween strategy using stock indices, but the results of this paper show that there may be other ways of investing to make even more profit. For Germany, stocks that show a (much) more significant Halloween effect than the index itself are BASF, K+S, MAN and TUI.

6.2 Suggestions for further research

This paper focused on the German stock market using data from the largest index in Germany, the DAX. As this only shows the magnitude of the Halloween effect in Germany, it would be interesting to also investigate other indices both within Germany and other countries. If it turns out that the Halloween effect is likely to be driven by only a handful of companies in other indices as well, the way how the Halloween effect is investigated may change. The focus could be more on the micro level instead of the macro level, because several important question can be answered on this level. Another suggestion for further research is to investigate more stock characteristics that may impact the Halloween effect to get an even better understanding of the anomaly. Although there is a huge amount of literature concerning the Halloween effect, this paper shows that there is still more research to be done, especially on the micro level.

References

Andrade, S. C., Chhaochharia, V., & Fuerst, M. E. (2013). "Sell in May and Go Away" Just Won't Go Away. *Financial Analysts Journal*, *69*, 94–105.

Arendas, P., Malacka, V., & Schwarzova, M. (2018). A Closer Look at the Halloween Effect: The Case of the Dow Jones Industrial Average. *International Journal of Financial Studies*, *6*(2), 42.

Borges, M. R. (2010). Efficient market hypothesis in European stock markets. *European Journal of Finance*, *16*(7), 29–32.

Bouman, S., & Jacobsen, B. (2002). The Halloween Indicator, "Sell in May and Go Away": Another Puzzle. *American Economic Review*, *92*(5), 1618–1635.

Cajueiro, D. O., & Tabak, B. M. (2004). The Hurst exponent over time: Testing the assertion that emerging markets are becoming more efficient. *Physica A: Statistical Mechanics and Its Applications*, *336*(3–4), 521–537.

Cao, M., & Wei, J. (2005). An Expanded Study on the Stock Market Temperature Anomaly. *Research in Finance*, *22*, 73–112.

Carrazedo, T., Curto, J. D., & Oliveira, L. (2016). The Halloween effect in European sectors. *Research in International Business and Finance*, *37*, 489–500.

Dichtl, H., & Drobetz, W. (2014). Are stock markets really so inefficient? The case of the "Halloween Indicator." *Finance Research Letters*, *11*(2), 112–121.

Dichtl, H., & Drobetz, W. (2015). Sell in May and Go Away: Still good advice for investors? *International Review of Financial Analysis*, *38*, 29–43.

Dzhabarov, C., & Ziemba, W. T. (2010). Do Seasonal Anomalies Still Work? *The Journal of Portfolio Management*, *36*(3), 93–104.

Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, *25*(2), 383–417.

Fama, E. F. (1998). The comments of Market efficiency, long-term returns, and behavioral finance. *Journal of Financial Economics*, *49*, 283–306.

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance*, *XLVII*(2).

Fiore, C., & Saha, A. (2015). A Tale of Two Anomalies: Higher Returns of Low-Risk Stocks and Return Seasonality. *The Financial Review*, *50*, 257–273.

Grossman, S. J., & Stiglitz, J. E. (1976). Information and Competitive Price Systems. *The American Economic Review*, *66*(2), 246–253.

Haggard, K. S., Jones, J. S., & Witte, H. D. (2015). Black cats or black swans? Outliers, seasonality in return distribution properties, and the Halloween effect. *Managerial Finance*, *41*(7), 642–657.

Haggard, K. S., & Witte, H. D. (2010). The Halloween effect: Trick or treat? *International Review of Financial Analysis*, *19*(5), 379–387.

Hamid, K., Suleman, M. T., Shah, S. Z. A., & Akash, R. S. I. (2017). Testing the Weak form of Efficient Market Hypothesis- Empirical Evidence from Asia-Pacific Markets. *International Research Journal of Finance and Economics*, *58*, 121–132.

Hansen, P. R. (2005). A test for superior predictive ability. *Journal of Business and Economic Statistics*, *23*(4), 365–380.

Hirshleifer, D., Jiang, D., & DiGiovanni, Y. M. (2020). Mood beta and seasonalities in stock returns. *Journal of Financial Economics*, *137*(1), 272–295.

Hong, H., & Yu, J. (2009). Gone fishin': Seasonality in trading activity and asset prices. *Journal of Financial Markets*, *12*(4), 672–702.

Jacobsen, B., Mamun, A., & Visaltanachoti, N. (2005). Seasonal, Size and Value Anomalies. *Working Paper, Massey University, University of Saskatchewan*.

Jacobsen, B., & Marquering, W. (2008). Is it the weather? *Journal of Banking and Finance*, *32*(4), 526–540.

Jacobsen, B., & Marquering, W. (2009). Is it the weather? Response. *Journal of Banking and Finance*, *33*(3), 583–587.

Jacobsen, B., Molchanov, A., & Zhang, C. (2019). Vacation behaviours and seasonal patterns of stock market returns. *Working Paper*.

Jacobsen, B., & Visaltanachoti, N. (2009). The Halloween Effect in U.S. Sectors. *The Financial Review*, *44*, 437–459.

Kamstra, M. J., Kramer, L. A., & Levi, M. D. (2003). Winter Blues: A SAD Stock Market Cycle. *The American Economic Review*, *93*(1), 324–343.

Kamstra, M. J., Kramer, L. A., Levi, M. D., & Wermers, R. (2017). Seasonal Asset Allocation: Evidence from Mutual Fund Flows. In *Journal of Financial and Quantitative Analysis* (Vol. 52, Issue 1, pp. 71–109). Cambridge University Press.

Kaustia, M., & Rantapuska, E. (2016). Does mood affect trading behavior? *Journal of Financial Markets*, 1–26.

Kelly, P. J., & Meschke, F. (2010). Sentiment and stock returns: The SAD anomaly revisited. *Journal of Banking and Finance*, *34*(6), 1308–1326.

Konak, F., & Şeker, Y. (2014). The Efficiency of Developed Markets: Empirical Evidence from FTSE 100. *Journal of Advanced Management Science*, *2*(1), 29–32.

Lintner, J. (1965). The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets. *Review of Economics and Statistics*, *47*(1), 13–37.

Lloyd, R., Zhang, C., & Rydin, S. (2017). The Halloween Indicator is More a Treat than a Trick. *Journal of Accounting and Finance*, *17*, 96–108.

Lucey, B. M., & Zhao, S. (2008). Halloween or January? Yet another puzzle. *International Review of Financial Analysis*, *17*(5), 1055–1069.

Maberly, E. D., & Pierce, R. M. (2004). Stock Market Efficiency Withstands another Challenge: Solving the "Sell in May/Buy after Halloween" Puzzle. *American Economic Review*, *1*, 29–46.

Malkiel, B. G. (2003). The Efficient Market Hypothesis and Its Critics. *Journal of Economic Perspectives*, *17*(1), 59–82.

O'Brien, M. A., Brailsford, T., & Gaunt, C. (2010). Interaction of size, book-to-market and momentum effects in Australia. *Accounting and Finance*, *50*(1), 197–219.

Risso, W. A. (2009). The informational efficiency: The emerging markets versus the developed markets. *Applied Economics Letters*, *16*(5), 485–487.

Schleifer, A. (2000). Inefficient Markets: An Introduction To Behavioral Finance. *New York: Oxford University Press*.

Schwert, G. W. (2003). Anomalies and Market Efficiency. *Handbook of the Economics of Finance*, *1*, 939–974.

Sharpe, W. F. (1964). Capital asset prices: A theory of market equilibrium under conditions of risk. *Journal of Finance*, *19*, 425–442.

Siriopoulos, C., & Giannopoulos, P. (2006). Market Efficiency in the Greek Stock Exchange: The Halloween Effect. *University of Piraeus*, *56*(2), 75–88.

Storm, S., & Naastepad, C. W. M. (2015). Crisis and recovery in the German economy: The real lessons. *Structural Change and Economic Dynamics*, *32*, 11–24.

Sullivan, R., Timmermann, A., & White, H. (2001). Dangers of data mining: The case of calendar effects in stock returns. *Journal of Econometrics*, *105*, 249–286.

Swagerman, D., & Novakovic, I. (2010). Multi-National Evidence on Calendar Patterns in Stock Returns: An Empirical Case Study On Investment Strategy And the Halloween Effect. *The International Journal of Business and Finance Research*, *4*, 23–44.

Swinkels, L., & van Vliet, P. (2012). An Anatomy of Calendar Effects 1 We would like to thank An Anatomy of Calendar Effects. *Journal of Asset Management*, *13*(4), 271–286.

Wachtel, S. B. (1942). Certain Observations on Seasonal Movements in Stock Prices. *The Journal of Business of the University of Chicago*, *15*(2), 184–193.

Witte, H. D. (2010). Outliers and the Halloween Effect: Comment on Maberly and Pierce. *Econ Journal Watch*, *7*, 91–98.

Yen, G., & Lee, C.-F. (2008). Efficient Market Hypothesis (EMH): Past, Present and Future *. *Review of Pacific Basin Financial Markets and Policies*, *11*(2), 305–329.

Zhang, C. Y., & Jacobsen, B. (2021). The Halloween indicator, "Sell in May and Go Away": Everywhere and all the time. *Journal of International Money and Finance*, *110*.

Appendix

Appendix A

TABLE 8: THE ANALYZED COMPANIES

Company	Time period	Number of years
Adidas	1996-2020	24
Allianz	1988-2020	32
BASF	1988-2020	32
Bayer	1988-2020	32
Beiersdorf	1988-2020	32
BMW	1988-2020	32
Commerzbank	1988-2020	32
Continental	1988-2020	32
Daimler	1998-2020	22
Deutsche Bank	1988-2020	32
Deutsche Lufthansa	1988-2020	32
Deutsche Telekom	1997-2020	23
E.ON SE	1988-2020	32
Fresenius	1992-2020	28
Fresenius Medical Care	1996-2020	24
Hannover RE	1995-2020	25
HeidelBergCement	1988-2020	32
Henkel	1988-2020	32
Infineon Technologies	2000-2020	20
K+S	1988-2020	32
Linde plc	1992-2020	28
MAN	1988-2020	32
Merck	1995-2020	25
MLP	1990-2020	30
Munich Re	1988-2020	32
ProSiebenSat.1 Media	1997-2020	23
TUI	1988-2020	32
RWE	1988-2020	32
Salzgitter	1988-2020	32
SAP	1989-2020	31
Siemens	1988-2020	32
ThyssenKrupp	1988-2020	32
Volkswagen Group	1988-2020	32

Table 8 presents the stocks that satisfy the three conditions as described in Chapter 4.1 The time period for which the analysis can be performed, and associated number of years are also presented. For several companies, only a part of the full period (1988-2020, 32 years) can be analyzed. One reason is that some companies only went public after 1988. For example, Adidas went public in November 1995 and price data is available since the beginning of 1996. Therefore, only 24 years can be analyzed for this company. Another reason is that some companies are simply founded after 1988. For example, Infineon Technologies was founded in 1999 and went public in 2000. Therefore, only 20 years can be analyzed for this company.

TABLE 9: SELECTION OF ALL THE COMPANIES

	Included in DAX	**Original company still exists**	**At least 20-year data available after 1988**	**Note**
Adidas	1998-2020	yes	yes	
Allianz	1988-2020	yes	yes	
Altana	2002-2007	no	yes	company still exists, but delisted from publicly trading in 2010
Arcandor	1988-2001	no	yes	former Karstadt and later KarstadtQuelle, bankrupted in 2009
BASF	1988-2020	yes	yes	
Bayer	1988-2020	yes	yes	
Beiersdorf	2008-2020	yes	yes	
BMW	1988-2020	yes	yes	
Ceconomy	1988-2012	no	yes	former Kaufhof and later Metro
Commerzbank	1988-2018	yes	yes	
Continental	1988-1996, 2003-2008, 2013-2020	yes	yes	
Covestro	2018-2020	yes	no	
Daimler	1998-2020	yes	yes	former Daimler-Benz and later DaimlerChrysler
Degussa	1988-2002	no	no	former Degussa and later Degussa-Hüls, acquired by RAG in 2006
Delivery Hero	Since 2020	yes	no	
Deutsche Babcock	1988-1995	no	no	reorganized into Babcock Borsig in 1996
Deutsche Bank	1988-2020	yes	yes	
Deutsche Börse	2002-2020	yes	no	
Deutsche Lufthansa	1988-2020	yes	yes	excluded in June 2020
Deutsche Post	2001-2020	yes	no	
Deutsche Postbank	2006-2009	yes	no	
Deutsche Telekom	1996-2020	yes	yes	
Deutsche Wohnen	Since 2020	yes	no	
Dresdner Bank	1988-2001	no	no	acquired by Commerzbank in 2008
E.ON SE	1988-2020	yes	yes	former Veba and VIAG
Epcos	2000-2002	no	no	acquired by TDK Electronics in 2008
Fresenius	2009-2020	yes	yes	
Fresenius Medical Care	1999-2020	yes	yes	
GEA Group	1990-1996	no	no	former Metallgesellschaft
Hannover Re	Only 2009	yes	yes	
HeidelbergCement	2010-2020	yes	yes	
Henkel	1988-2020	yes	yes	
Hoechst	1988-1999	no	no	since 2005 a wholly owned subsidiary of Sanofi
Hypo Real Estate	2005-2008	yes	no	
HypoVereinsbank	1988-2005	no	yes	former Bayer. Hypobank and Bayer. Vereinsbank, since 2008 a wholly owned subsidiary of UniCredit

Infineon Technologies	2000-2009, 2009-2020	yes	yes	excluded in March but included again in September
K+S	2008-2016	yes	yes	
Lanxess	2012-2015	yes	no	
Linde plc	1992-2020	yes	yes	former Linde
MAN	1988-2012	yes	yes	
Merck	2007-2020	yes	yes	
MLP	2001-2003	yes	yes	
MTU Aero Engines	2019-2020	yes	no	
Munich RE	1996-2020	yes	yes	
ProSiebenSat.1 Media	2016-2018	yes	yes	
TUI	1990-2008	yes	yes	former Preussag
RWE	1988-2020	yes	yes	
Salzgitter	2008-2010	yes	yes	
SAP	1995-2020	yes	yes	
Schering	1988-2006	no	no	acquired by Bayer in 2006
Siemens	1988-2020	yes	yes	
ThyssenKrupp	1988-2019	yes	yes	former Thyssen
Vodafone	1988-2000	no	no	former Mannesmann
Volkswagen Group	1988-2020	yes	yes	
Vonovia	2015-2020	yes	no	
Wirecard	2018-2020	yes	no	excluded in August 2020

Table 9 presents the selection of all the companies that were once included in the DAX during the time period 1988 to 2020. The second column present for how long the particular company has been included in the DAX. The third column states whether the original company still exists and whether its shares are publicly traded. The fourth column states whether there is at least 20 years of price data available since 1988. The fifth column present notes regarding the particular company. The information is retrieved from Thomson Reuters Eikon, in particular the Leavers & Joiners tab of the DAX and company-specific information about each individual company. The table is based on the work of Arendas et al. (2018).

Appendix B

TABLE 10: DESCRIPTIVE STATISTICS RETURNS DAX 30

Firm	Mean	Sd	Minimum	Maximum	Skewness	Kurtosis
DAX	0,75	5,94	-20,62	20,07	-0,55	4,12
DAX winter returns	1,52	5,56	-19,51	20,07	-0,44	3,72
DAX summer returns	-0,02	6,22	-20,62	15,42	-0,57	4,51

Table 10 presents the descriptive statistics of the DAX 30. The descriptive statistics are the mean, standard deviation, minimum, maximum, skewness and kurtosis. The numbers are rounded to two decimals.

Appendix C

TABLE 11: DESCRIPTIVE STATISTICS WINTER RETURNS ANALYZED COMPANIES

Firm	Mean	Sd	Minimum	Maximum	Skewness	Kurtosis
Adidas	2,51	8,36	-19,53	23,35	-0,22	2,99
Allianz	1,39	8,43	-29,04	47,55	0,43	8,45
BASF	2,01	7,10	-24,10	23,77	-0,19	4,34
Bayer	1,41	7,64	-23,77	31,98	-0,11	4,78
Beiersdorf	1,54	5,66	-15,41	15,87	0,15	2,97
BMW	1,78	8,23	-23,60	28,37	0,09	3,77
Commerzbank	0,95	11,87	-49,93	55,41	0,27	8,26
Continental	1,91	10,06	-53,66	53,24	-0,54	11,34
Daimler	0,88	9,71	-31,04	39,00	0,18	4,76
Deutsche Bank	1,34	9,95	-30,75	58,50	0,79	8,61
Deutsche Lufthansa	1,48	8,31	-27,99	28,24	-0,17	3,77
Deutsche Telekom	0,91	9,07	-26,06	44,55	0,93	7,10
E.ON SE	1,16	6,73	-22,96	21,83	-0,45	4,30
Fresenius	2,43	9,50	-22,02	65,82	1,63	14,06
Fresenius Medical Care	1,62	8,58	-23,55	45,55	1,35	8,53
Hannover RE	1,73	8,61	-23,20	38,52	0,82	6,18
HeidelBergCement	1,54	9,17	-39,71	30,25	-0,69	5,66
Henkel	1,35	6,73	-22,23	19,83	-0,18	3,79
Infineon Technologies	2,23	18,76	-44,22	134,20	2,94	23,00
K+S	2,63	9,74	-29,23	55,67	0,71	7,50
Linde plc	1,92	7,96	-18,81	51,04	1,49	11,81
MAN	2,63	8,70	-25,15	35,06	0,19	4,76
Merck	1,38	7,65	-19,93	24,62	-0,09	3,44
MLP	2,44	12,76	-40,92	54,07	0,56	5,79
Munich Re	0,88	8,63	-33,73	59,29	1,00	14,45
ProSiebenSat.1 Media	2,58	18,51	-42,80	88,88	1,63	9,13
TUI	1,94	13,20	-42,50	101,10	2,16	20,07
RWE	0,63	8,32	-31,47	25,61	-0,19	4,04
Salzgitter	1,91	9,61	-31,01	30,77	0,14	3,90
SAP	2,63	10,63	-34,54	57,37	0,97	8,03
Siemens	1,65	8,47	-23.47	32,04	0,00	4,18
ThyssenKrupp	1,42	10,32	-46,59	32,93	-0,14	5,43
Volkswagen Group	1,45	9,51	-31,88	25,20	-0,40	3,89
DAX 30	1,52	5,56	-19,51	20,07	-0,44	4,51

Table 11 presents the descriptive statistics of all companies that are being analyzed in the winter. The descriptive statistics are the mean, standard deviation, minimum, maximum, skewness and kurtosis. The numbers are rounded to two decimals.

TABLE 12: DESCRIPTIVE STATISTICS SUMMER RETURNS ANALYZED COMPANIES

Firm	Mean	Sd	Minimum	Maximum	Skewness	Kurtosis
Adidas	0,35	7,86	-24,56	16,20	-0,49	3,46
Allianz	-0,09	9,26	-37,80	31,90	-0,48	5,47
BASF	-0,51	7,14	-21,16	24,04	-0,05	3,54
Bayer	-0,25	7,73	-26,63	19,14	-0,46	3,43
Beiersdorf	0,43	6,68	-18,61	18,18	0,08	3,40
BMW	0,03	8,54	-27,37	22,76	-0,20	3,37
Commerzbank	-1,04	11,23	-40,00	32,53	-0,25	4,42
Continental	0,16	9,93	-39,79	37,55	-0,23	4,97
Daimler	-0,24	9,72	-27,10	27,67	-0,12	3,33
Deutsche Bank	-0,82	9,95	-39,41	26,27	-0,31	3,97
Deutsche Lufthansa	-0,53	10,32	-37,87	22,23	-0,22	2,98
Deutsche Telekom	-0,37	7,74	-32,64	27,69	-0,61	5,46
E.ON SE	-0,23	7,22	-24,08	28,88	-0,24	4,60
Fresenius	0,45	9,03	-29,49	59,09	1,04	13,13
Fresenius Medical Care	-0,18	8,54	-32,31	35,87	0,13	7,43
Hannover RE	0,47	8,17	-35,09	30,51	-0,23	6,37
HeidelBergCement	-0,08	9,49	-21,90	38,48	0,46	4,20
Henkel	0,29	6,16	-16,29	17,00	-0,25	3,02
Infineon Technologies	-0,10	15,56	-50,49	75,21	0,50	7,73
K+S	-0,97	10,19	-42,94	-27,12	-0,51	4,70
Linde plc	0,60	6,53	-25,74	27,18	-0,09	5,71
MAN	-1,08	8,91	-36,01	25,87	-0,64	5,26
Merck	0,66	7,73	-25,42	26,11	-0,02	3,96
MLP	-0,28	12,52	-50,72	48,73	-0,24	6,06
Munich Re	0,84	8,68	-37,53	43,03	0,30	7,36
ProSiebenSat.1 Media	0,33	17,31	-57,39	112,10	1,72	15,21
TUI	-0,94	10,14	-34,24	27,04	-0,39	3,49
RWE	0,59	8,37	-31,31	32,43	-0,20	5,25
Salzgitter	-0,49	10,27	-34,95	35,01	0,06	3,83
SAP	1,30	11,68	-39,89	81,76	1,26	14,78
Siemens	0,15	9,24	-26,78	39,48	0,25	5,29
ThyssenKrupp	-0,68	10,20	-37,72	24,60	-0,49	3,76
Volkswagen Group	0,80	11,09	-51,37	46,15	-0,15	6,26
DAX 30	-0,02	6,22	-20,62	15,42	-0,57	3,72

Table 12 presents the descriptive statistics of all companies that are being analyzed in the summer. The descriptive statistics are the mean, standard deviation, minimum, maximum, skewness and kurtosis. The numbers are rounded to two decimals.

Appendix D

TABLE 13: OLS REGRESSION STOCK CHARACTERISTICS IF BETA = 0

	(1)
VARIABLES	price
winter	1.669***
	(0.224)
Constant	0.0463
	(0.158)
Observations	5,981
R-squared	0.009

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 14: OLS REGRESSION STOCK CHARACTERISTICS IF BETA = 1

	(1)
VARIABLES	price
winter	1.838***
	(0.281)
Constant	-0.159
	(0.198)
Observations	5,781
R-squared	0.007

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix E

TABLE 15: OLS REGRESSION STOCK CHARACTERISTICS IF SIZE = 0

	(1)
VARIABLES	price
winter	2.082***
	(0.259)
Constant	-0.239
	(0.183)
Observations	6,102
R-squared	0.011

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 16: OLS REGRESSION STOCK CHARACTERISTICS IF SIZE = 1

	(1)
VARIABLES	price
winter	1.396***
	(0.246)
Constant	0.144
	(0.174)
Observations	5,660
R-squared	0.006

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix F

TABLE 17: OLS REGRESSION STOCK CHARACTERISTICS IF BTM = 0

	(1)
VARIABLES	price
winter	1.585***
	(0.257)
Constant	0.170
	(0.182)
Observations	5,941
R-squared	0.006

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

TABLE 18: OLS REGRESSION STOCK CHARACTERISTICS IF BTM = 1

	(1)
VARIABLES	price
winter	1.923***
	(0.249)
Constant	-0.285
	(0.176)
Observations	5,821
R-squared	0.010

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1