The Sell-in-May Effect in International Stock Markets

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Abstract

Several studies have presented evidence for higher returns in stock markets from the beginning of November to the end of April compared to the rest of the year. This phenomenon is well known as the Sell-in-May effect. The main focus of this thesis is to investigate whether the Sell-in-May effect still exists in financial markets and whether the power of the effect deviates between time and markets. Additionally, we investigate discrepancies in risk and return between the summer and winter months, as well as the January effect, in order to examine whether these explanations could help us understand the existence of the Sell-in-May effect. In an effort to examine if the investors could exploit and profit from the market anomaly, we developed and simulated a trading strategy based on the Sell-in-May effect and performed various statistical tests against the Buy-and-Hold benchmark strategy. The output from the regression model showed evidence of an existing Sell-in-May effect. Neither the January effect nor differences in risk proved to be viable explanations for the existence of the effect. Further results indicated that the Sell-in-May strategy outperformed the Buy-and-Hold strategy in most scenarios, indicating that investors could exploit and profit from the market anomaly.

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1 Introduction

In the first section of the introduction, we will introduce the reader to the background of our research subject, in addition to how our subject is connected to previous studies. Subsequently, in the next section, we lay out the problem formulation which addresses the various problems this thesis will focus on.

1.1 Background

The term “seasonality" refers to the tendency for securities to perform better at certain times of the year and worse at others. Days of the week, months of the year, six-month intervals, and even multi-year timeframes can all be used as a measure. Seasonalities or patterns in stock markets include the holiday effect, Monday effect, January effect, and Sell-in-May effect, to name a few (Marret & Worthington, 2009; Wang et al., 1997; Sun & Tong, 2010; Bouman & Jacobsen, 2002). We consider the latter seasonality to be the most compelling, hence the Sell-in-May effect will be the primary focus of our thesis.

In terms of stock market returns, it has long been assumed that stocks tend to perform far better during the winter months (November-April), compared to the summer months (May-October) (Bouman & Jacobsen, 2002). There is an old saying that dates as far back as 1697 which illustrates this common wisdom: “Sell in May and go away”. May marks the start of a period in which investors expect to get reduced returns. The trading strategy suggests investors would be better off selling their stocks/positions and switching to cash/holding bonds from May through November (Bouman & Jacobsen, 2002).

The expression has two different endings. Sometimes the saying has a prolonged ending to “Sell in May and go away, but come back on St Leger's day”. Another is “Sell in May and go away, but remember to buy back in September ". According to Bouman & Jacobsen (2002), the first ending refers to a horse race that dates back to 1778 in England, which takes place every mid-September.

Another more widely used term for the same phenomenon is the "Halloween indicator" or "Halloween effect," which was coined by O'Higgins & Downes (1990) and recommends that investors should return to the market around the beginning of November, thus splitting the year into six summer months and six winter months. The existence of such a market anomaly is contradicting the famous Efficient Market Hypothesis (EMH) of the Nobel Prize winner Fama (1970). Fama's EMH claims that in efficient markets, it is unattainable for investors to acquire and achieve advantages from publicly available information (Fama, 1970).

There exists a variety of anomalies in the stock markets, and the Sell-in-May effect is just one of many. Anomalies are discrepancies or inconsistencies from the classical asset-pricing theories that can generate investment possibilities for investors (Schwert, 2003). From the moment a market anomaly occurs that creates possibilities and opportunities for investors, the advantages start to diminish and disappear (Fama, 1970). As time goes on, more investors begin to exploit the strategy, until it reaches a point when there is no longer any profit left from the opportunity (Jensen, 1978). Correspondingly, Marquering, et al. (2006), concluded in their studies that calendar-related anomalies such as the holiday effect, January effect, and the time of the month effect, disappear as soon as they become known to the public. The fact that market anomalies diminish over time as they become publicly known, is very much aligned with the EMH. Be that as it may, the Sell-in-May effect has been well-known for decades, and has still not disappeared as other anomalies generally do (Bouman & Jacobsen, 2002).

The first known academic research that documented the Sell-in-May anomaly was the study of Bouman & Jacobsen (2002). By using data from January 1970, until August 1998, their seminal study provided evidence of a Sell-in-May effect in 36 out of 37 countries. Their results were later confirmed by the studies of Andrade et al. (2013), and Degenhardt & Auer (2018). Bouman & Jacobsen (2002) discovered that the divergence in stock market returns was significant. The effect was particularly present in Europe, where the mean return in the summer months did not surpass 2% for any country besides Denmark. In comparison, the winter months showed a mean return that exceeded 8% in all countries.

Researchers on this subject have yet to come up with a precise explanation for why the Sell-in-May anomaly exists. Data mining, liquidity, length of vacations, and risk differences were possible explanations that Bouman & Jacobsen (2002) investigated. Only the time and length of vacations showed statistically significant results and other explanations had to be rejected.

In addition, Bouman & Jacobsen (2002) also made inquiries on whether the January effect could help explain the Sell-in-May anomaly. The January effect is another well-known calendar anomaly that was first documented as early as 1942 by Wachtel (1942) and suggests that January yields significantly higher returns on average compared to other calendar months. Because January is included in the winter months, it is unclear whether the Sell-in-May effect is driven mainly by large January returns. As a result, multiple research has suggested the January effect as a possible explanation for the Sell-in-May effect. However, the studies of Haggard & Witte (2010) found the Sell-in-May effect to be robust in consideration of outliers, The January effect, and transaction costs.

1.2 Problem Formulation

This thesis is inspired by the research paper written by Bouman & Jacobsen in 2002. Although Bouman & Jacobsen (2002) provide clear evidence for the existence of the Sell-in-May effect between 1970 and 1998, further research regarding this subject is still required. Fama (1970) stated that seasonal effects will diminish once the effect is known to the public. To examine the existence of the Sell-in-May effect we replicate the results from previous studies regarding the anomaly. In addition, we extend our study by dividing the Standard & Poor's 500 (S&P 500) and Dow Jones Industrial Average (DJIA) into three sub-periods, as well as applying the Fama-French 5-factor model on all indices and countries to test whether additional risk factors may help explain the existence of the effect.

The first goal of our thesis aims to investigate the historical strength of the Sell-in-May effect by comparing different sub-periods. Second, we compare the Sell-in-May effect between various countries to examine whether the effect is still a worldwide phenomenon today, so that our results may be applicable to the market in general. If our results show that the Sell-in-May effect still exists today, Fama's statement has to be questioned. Third, our study will also test whether or not the Sell-in-May effect is just the January effect in disguise. Meaning how much the January effect contributes to the Sell-in-May effect. To test for these effects, we will apply two Ordinary Least Squares (OLS) regression models.

Fourth, we examine the risk-return relationship between the winter months (November-April) and summer months (May-October). This relationship will be investigated to see whether the high returns during the winter months can be explained by a higher level of risk. If the results indicate that the higher returns in the winter period are accompanied by a higher level of risk, this might contribute as a possible explanation for the existence of a Sell-in-May effect. The standard deviation will be used as a risk measurement.

Lastly, we construct and compare two different investment strategies in order to examine whether the investor can exploit and profit from the anomaly. The first strategy constitutes the Sell-in-May strategy and the second strategy will be a traditional Buy-and-Hold strategy. Further, the Sharpe ratio is calculated for each strategy to assess which of the two strategies offers the best risk-adjusted return. In addition to Sharpe ratio, the alpha coefficients for the Capital Asset Pricing Model (CAPM) and the Fama-French 5-factor model will be estimated for each respective strategy. Jensen`s alpha coefficients from the CAPM indicate whether the Sell-in-May strategy under- or outperformed the Buy-and-Hold strategy, given its level of risk. Whilst alpha coefficients from the Fama-French 5-factor model indicate whether the Sell-in-May anomaly`s existence can be explained by additional risk factors.

2 Literature Review

In this chapter, previous research on the topic is presented to give the reader a comprehensive overview and grasp of the subject and essential concepts. The literature review is structured in such a way that it begins with the underlying theories and ends up with the main topics of this thesis.

2.1 The Efficient Market Hypothesis

Fama (1970) developed the Efficient Market Hypothesis (EMH). In the same paper, he also presented a definition of what is meant by an efficient market. According to Fama (1970), the allocation of ownership of the economy's capital stock is the primary role of the capital market. For a market to be ideal and efficient he stated that the prices should provide accurate signals for resource allocation and that the prices "fully reflect" the available information (Fama, 1970). It has also been stated that securities markets are efficient. "Securities markets are efficient in the reflection of news/information about particular stocks or about the overall market as a whole" (Ying et al., 2019, p. 3). When it comes to the available information, there are three basic types or levels of market efficiency, weak, semi-strong, and strong (Fama, 1970).

In the weak form of an efficient market, investors cannot beat the market by studying past prices, which means that past prices cannot be used to predict future prices (Fama, 1970). When the current prices are the only available financial information, there will not be any abnormal returns from investing in these financial assets (Titan, 2015). The semi-strong form states that all public information that exists on the market reflects the prices of financial assets (Degutis & Novickyte, 2014). With additional information like historical prices and other historical information, the prices of financial assets tend to fluctuate without biases to reflect any new public information provided in the market (Titan, 2015). In the strong form of EMH, all information is accounted for in the current stock price. What separates the strong form from the semi-strong form is that in addition to the public information that is available, private information is also accounted for, including insider information (Titan, 2015). With this type of additional information, there is no other type of information that may give an investor any kind of advantage compared to other investors in the market (Ying et al., 2019).

2.2 Market Anomalies

In 1942 Sidney Wachtel wrote a paper on seasonal movements in stock prices, known as calendar anomalies. At that time there had not been conducted a lot of research concerning this topic (Wachtel, 1942). In 2004, Andrew Lo developed the Adaptive Market Hypothesis (AMH). The AMH differs from the traditional EMH by accounting for seasonal differences in the loss/return relationship, meaning that the degree of efficiency will vary in different periods (Lo, 2004). Implementing the AMH developed by Lo (2004), Urquhart & McGroarty (2014) tested four of the most known calendar anomalies using the Dow Jones Industrial Average in the period 1900 to 2013. These four calendar anomalies were the Monday effect, January effect, turn-of-the-month, and the Sell-in-May effect (Urquhart & McGroarty, 2014). Their results show that all of these four anomalies' behavior varies over time, being in accordance with the AMH (Urquhart & McGroarty, 2014).

2.2.1 January Effect

The first two weeks of January are well known for generating abnormally high stock returns compared to other calendar months (Moller & Zilca, 2008). In recent years this phenomenon has been named the January effect and it is one of the most publicly known calendar anomalies (Sun & Tong, 2010). In 1976 Rozeff & Kinney conducted a study concerning the existence of the January effect, using data from the New York Stock Exchange from 1904 to 1974, excluding the years 1929 to 1940. By comparing the mean return for the different months, Rozeff & Kinney (1976) concluded that January would outperform the other months. Since the main purpose of Rozeff & Kinney's (1976) study was to demonstrate the existence of the January effect, the authors did not seek to explain the existence of the effect.

In a paper published in 1983, Reinganum provided a possible solution to the existence of the January effect. Reinganum (1983) suspected the abnormally high returns at the beginning of

January could be associated with tax-loss selling. Branch (1977) came to the conclusion that tax-loss selling does not impact the general level of stock prices in an average year. However, stocks experience a higher selling pressure at the end of the year, leading to a rise in prices at the beginning of January (Branch, 1977). Investors can therefore sell their stocks at a loss at the end of December to reduce the capital gain earned on their investment and reinvest their capital at the beginning of January (Grinblatt & Moskowitz, 2004).

Another explanation for the existence of the January effect is window-dressing. Together with tax-loss selling, this explanation is one of the most prominent explanations for the existence of the January effect (Starks et al., 2006). Window-dressing is when an investor or fund manager alters the existing portfolio by eliminating the losers, in order to impress sponsors (Lakonishok et al., 1991). In the paper, *The January Effect*, Haug & Hirschey (2006) updated the evidence on the January effect in value-weighted returns and equal-weighted returns by taking the window-dressing hypothesis into account. Based on their results, the persistence of the January effect was largely confined to small-cap stocks compared to large-cap stocks, indicating that the January effect is a small-cap phenomenon (Hauge & Hirschey, 2006).

2.3 Existence of the Sell-in-May Effect

This paper will investigate the market anomaly called the Sell-in-May effect, which is the tendency for stocks to yield higher returns on average in the period stretching from November 1 to April 30 (hereafter defined as winter), compared to the remaining months (hereafter defined as summer). As mentioned earlier, the first extensive study on this topic was published by Bouman & Jacobsen (2002), who examined the Sell-in-May effect in 37 countries. Their studies provided evidence of the market anomaly occurring in 36 of 37 countries, the only exception being New Zealand. In the following years of their publication, plenty of other researchers examined the Sell-in-May effect as well. This section will present an overview of these studies, followed by other studies that question the existence of such effects.

Andrade et al. (2013) investigated the same sample as Bouman & Jacobsen (2002), in addition to an out-of-sample with a newer time period, 1998 to 2012. Their study was able to confirm the results and concluded that the average winter return is 10 percentage points above the average summer return. Even after the global financial crisis of 2008, the Sell-in-May effect is still prevalent, according to studies by Lloyd et al. (2017). Given the severity of the crisis, it was presumed that the Sell-in-May effect might fade in such tumultuous times. The researchers did, however, confirm the presence of the Sell-in-May effect, finding it in 34 out of the 35 countries studied. Instead of looking at the differences between countries, Jacobsen & Visaltanachoti (2009) concentrated on the differences between market sectors. 17 sectors and 49 U.S industries were evaluated in the paper. Jacobsen & Visaltanachoti (2009) discovered that all sectors showed significantly higher winter returns compared with summer returns. Additionally, the results detected relatively large differences between the sectors. Consumer sectors were less affected than the production sectors, which experienced a much more powerful Sell-in-May effect on average.

According to Zhang & Jacobsen (2021), from a geographical standpoint, the Sell-in-May effect is relatively stronger in countries located in Europe, Asia, and North America as opposed to other areas. The authors also discovered that developed and emerging markets experience a stronger Sell-in-May effect compared to frontier and rarely studied markets. Although, we must note that Zhang & Jacobsen (2021) pointed out that this interesting finding might be caused by the limitation of available data from such markets. The studies of Swagerman & Novakovic (2010) could verify the existence of a Sell-in-May effect in both developed and emerging markets, although a stronger effect in the former.

There has also been conducted other research that cast doubt on the Sell-in-May effect`s existence. In 2004, Marberly & Pierce criticized the findings of Bouman & Jacobsen (2002). Marberly & Pierce (2004) claimed that the results were influenced by both the October 1987 stock market crash, in addition to the August 1998 collapse of hedge fund Long-Term Capital Management, since both occurred during the summer months. However, according to Haggard & Witte (2010), removing not just these two outliers, but also the next four most prominent outliers enhanced the Sell-in-May effect by more than 12 basis points. By looking at 20-year sub-periods, Lucey & Zhao (2008) studied the U.S stock market from 1926 to 2002. The authors discovered that the Sell-in-May effect is rarely observed, and when it is, it is solely due to the January effect. Conversely, Haggard & Witte (2010) demonstrated that these results are most likely due to the small sample size employed in the study. By examining longer subperiods and using updated data until 2008, Haggard & Witte (2010) confirms that the Sell-in-May effect is statistically significant and independent of the January effect from 1954 to

2008. Although their results conclude that there is no presence of a Sell-in-May effect between 1926 and 1953.

The studies of Siriopoulos & Giannopoulos (2006) argued that the Sell-in-May effect could be influenced by data outliers. Their study found no evidence of a Sell-in-May effect after controlling for outliers on data from the Greek stock market from October 1986 to December 2004. By using all available historical data for all stock market indices globally (62962 monthly observations), Zhang & Jacobsen`s study from 2021 appears to answer all skeptics once and for all. The scientists discovered that the 6-month return is on average 4 percentage points greater in the winter compared to the summer. For 89 of the 114 countries studied, mean returns are higher in the winter. For 42 countries, the results are statistically significant. The scientists conclude that the conflicting results are most likely due to sample selection. For the time being, this study appears to answer all skeptics.

2.4 Possible Explanations for the Sell-in-May Effect

Bouman & Jacobsen (2002) hypothesized several theories that could help explain the Sell-in-May effect. Data mining, economic significance, trade volume, January effect, sectors, interest rates, news, and length of vacations were all possibilities they focused on. In terms of calendar anomalies, data mining is a common explanation. Data mining can be defined as the errors which occur while assembling and analyzing substantial collections of raw data (Hand et al., 2000). According to the literature, well-known financial calendar anomalies should never be persistent in out-of-sample periods (Schwert, 2003). To avoid data mining, Bouman & Jacobsen (2002) used out-of-sample results in their computations. When it comes to data-driven anomalies like the Sell-in-May effect, we normally expect results to be inconsistent across countries and over longer periods. Nevertheless, because Bouman & Jacobsen's (2002) discoveries are consistent across nations and endure over time, results are considered robust, meaning they could discard data mining as a plausible explanation for the Sell-in-May effect (Bouman & Jacobsen, 2002). Anomalies can usually be explained in terms of economic significance by proposing transaction costs, implying that the expense of trading surpasses the potential economic rewards. Bouman & Jacobsen (2002), on the other hand, rejected this as a credible explanation because the Sell-in-May effect’s economic significance was insignificant.

Additionally, Bouman & Jacobsen (2002) also investigated whether trading volume and interest rates varied between the summer and winter months, and if so, whether this may help explain the existence of the effect. Interestingly, their findings suggested that in none of the 37 countries, neither trading volume nor interest rates were statistically significant. The hypothesis of time and length of vacations, however, turned out to be statistically significant, as these variables turned out to impact trading activity. Another scientific paper by Hong & Yu (2009) confirmed the same results that vacations negatively affected trading activity, and they revealed that due to summer vacations, stock returns were considerably lower during the summer months.

2.5 The Sell-in-May Trading Strategy

In their paper on the Sell-in-May effect, Bouman & Jacobsen (2002) also investigated if the Sell-in-May effect could be exploited as a trading strategy. The strategy was tested against a Buy-and-Hold strategy where investors only invested in the market portfolio. What separates the Sell-in-May strategy from the Buy-and-Hold, is that Bouman & Jacobsen's (2002) strategy was based on investing in the market portfolio from November to April, then switching to a risk-free asset from May to October. This strategy was expected to exploit the effect, providing the investors with a better and less risky investment opportunity (Bouman & Jacobsen, 2002). To compare the two strategies, they used the mean return and the standard deviation estimated from a sample of 18 countries. In 16 of the countries, the results showed that the Sell-in-May strategy would outperform the Buy-and-Hold strategy (Bouman & Jacobsen, 2002). For Jensen's alpha, the values for all countries were above zero, and the beta coefficient was well below 1 (Bouman & Jacobsen, 2002). They confirmed these results by comparing the cumulative frequency distribution between the two strategies. In their paper, they only plotted the cumulative frequency distribution for Italy. Bouman & Jacobsen (2002) still state that there were similar results for the other countries.

As a continuation of the study performed by Bouman & Jacobsen (2002), Haggard & Witte (2010) also tested whether the Sell-in-May strategy would outperform the Buy-and-Hold strategy. Their study examined a strategy where they were fully invested in the Buy-and-Hold fund (market), and a strategy consisting of investing in a Sell-in-May fund. The Sell-in-May fund would consist of the Buy-and-Hold fund from November to April, then 3-month T-bills from May to October (Haggard & Witte, 2010). To distinguish their study from Bouman & Jacobsen (2002), they implemented the Sharpe ratio as a risk-adjusted performance measurement. In their results, Haggard & Witte (2010) provided evidence that the Sell-in-May strategy would generate a Sharpe ratio that was significantly higher compared to the Buy-and-Hold strategy. Both Bouman & Jacobsen (2002) and Haggard & Witte (2010) concluded that the Sell-in-May effect could be implemented as a profitable trading strategy that would favor the investors.

3 Data Collection

In this section, the data employed to examine the Sell-in-May effect and the January effect will be presented. The data presented here will be fundamental for the empirical results obtained in chapter 5.

3.1 Description of Data

The data sample used in this thesis comprises monthly market return data from a total of 17 countries. For the US stock market, we have used data from two different indices, both the S&P 500 from 1870 to 2020 and the DJIA from 1896 to 2020, including the risk-free rate for these periods. Due to the long time horizon for the S&P 500 and the DJIA, we chose to divide the data into three sub-periods. The reason behind this is to be able to identify how the strength of the Sell-in-May effect deviates throughout history. A sub-period constitutes a period that is a subdivision of a longer period. To illustrate, the data sample for the S&P 500 is 150 years long, and we have divided this period into three sub-periods of equal lengths. Then each sub-period contains 50 years of data on monthly returns, sub-period 1 constitutes the first 50 years, sub-period 2 the next 50 years, and sub-period 3 the last 50 years.

For the remaining 16 countries (henceforth international countries), we downloaded the monthly total return data from the value-weighted MSCI reinvestment index found in Kenneth R. French - Data Library. However, this data did not contain any risk-free rates. Consequently, we were forced to use a separate source (Fred Economic Data) for obtaining the risk-free rate for each of the remaining countries. It is worth mentioning that this thesis uses long-term government bond yields with 10 years to maturity as a proxy for the risk-free rate. After downloading the risk-free rates, the next step in the process was to construct a time series object for each country, containing both the date, monthly return, and risk-free rate.
All computations were performed using the R-studio software tool. Because of limited data availability, countries' respective time series vary in length depending on how much historical data was available.

Additionally, in order to calculate alpha estimates from the Fama-French 5-Factor model, we have downloaded Fama/French developed 5-factors and Fama/French US 5-factors data from Kenneth R. French data library. We applied the developed 5-factors to the international countries and 5-factors to the US indices. The first recorded data on the US 5-factor sample started in 1963, therefore we had to exclude alpha estimations for both sub-period 1 and 2.

3.2 Chosen Data

The reason behind dividing the US data from both the S&P 500 and DJIA into three sub-periods is as mentioned earlier, primarily to gain a better understanding of how the Sell-in-May effect has deviated throughout time. The length of each sub-period for the S&P 500 is 600 observations which constitute 50 years, and for the DJIA each period is approximately 40 years or around 500 observations. Lucey & Zhao's (2008) study was criticized by Haggard & Witte (2010), for using too short sub-periods, which led to reduced power and statistical significance in their testing. As a result, we believe it is reasonable to adopt lengthier sub-periods for the US market (40 to 50 years). Because of limited data availability, the time series starting date varies between 1975 and 1991 for all international countries. The majority of the international countries investigated are European, with the exceptions of Australia, Canada, and Japan. Additionally, we should note that all countries covered in this thesis are classified as developed markets. Developed countries or markets are typically distinguished by a high level of economic growth and security.

4 Methodology

This chapter presents the statistical methodology as well as the hypotheses we developed in order to fully examine the Sell-in-May effect.

4.1 Statistical Methodology

4.1.1 Mean Return

Most studies conducted on this subject, including Bouman & Jacobsen's (2002) use continuously compounded returns when testing for the Sell-in-May effect. Since our raw data downloaded from Kenneth R. French data library is noted in simple returns, it is beneficial for our analysis to convert the simple returns into continuously compounded returns, before we start testing for the Sell-in-May effect ourselves. The formula for continuously compounded return, also known as the logarithmic return was constructed by (Ruppert, 2004), and is illustrated in equation 1 below.

$$R_t = ln(\frac{p_t}{p_{t-1}}) = ln(1 + R_t) \qquad (1)$$

Where R_t is the return at time t, ln denotes the natural logarithm, p_t equals price at time t and p_{t-1} is the price at time t - 1. In our case however, we do not have access to monthly prices, but rather the simple return for each month. We can see from equation 1 above that taking the natural logarithm of $(1 + R_t)$ also gives us continuously compounded returns (Ruppert, 2004).

4.1.2 Regression Models

In order to test for the Sell-in-May effect, the same regression models that Bouman & Jacobsen (2002) first developed are employed when conducting the statistical testing. Their methodology constructed a framework that has been adopted in multiple subsequent studies, including Jacobsen & Visaltanachoti (2009), and Andrade et al. (2013). In equation 2 below, we present regression model (1) which is applied to test for the Sell-in-May effect.

$$R_t = \mu + \delta_1 SIM_t + \varepsilon_t \tag{2}$$

R_t denotes the return for the index, μ represents the intercept, δ_1 is the coefficient estimate, SIM_t is the dummy variable for the Sell-in-May effect and ε_t is the error term. During the months of November to April, the dummy variable SIM_t equals 1, similarly during the months of May to October, it takes the value of 0. The regression determines if the average returns from November to April differ from the period May to October. The use of a dummy variable in the regression model enables us to depart from the standard random walk model (Bouman & Jacobsen, 2002).

$$SIM_t = \begin{cases} 1: November, December, January, February, March, April \\ 0: May, June, July, August, September, October \end{cases}$$

The intercept coefficient μ denotes the average return for months where the dummy variable equals 0, that is, from May to October. If the coefficient estimate δ_1 is positive, it implies that the average return is higher between November and April, indicating a Sell-in-May effect. If the coefficient δ_1 is negative, however, it signals that the average return is lower during the winter months compared to summer months. Such a result would be contradicting to the Sell-in-May effect. The positive coefficient estimate indicates the excess return for the winter period. Conversely, a negative delta denotes the excess return for the summer period.

Furthermore, the regression model is testing whether or not the Sell-in-May effect is of statistical significance. Similarly to Bouman & Jacobsen (2002), we are testing the statistical significance through t-values using a significance level of 10%. To determine whether their hypotheses were either rejected or accepted, the scientists used a critical t-value of 1.65 in their tests. In order to verify that the same t-value is correct for our analysis, we have checked this through the t-distribution. Firstly, we note that the test becomes a two-tailed test because it examines the difference between two separate sets. Since the number of observations for all countries' sample sizes exceeds 120, the degrees of freedom go to infinity (Beyer, 1968).
The crucial t-value at this level is 1.645, which is rounded up to 1.65 to match Bouman & Jacobsen's (2002) critical value. On top of that, in order to examine the Sell-in-May effect's variation in significance, we have also inserted significance thresholds of 0.05 (5%) and 0.01 (1%). These levels' critical values have also been extracted from the t-distribution, and they are 1.96 and 2.58, respectively.

In their studies, Bouman & Jacobsen (2002) suggested that the Sell-in-May effect could just turn out to be the January effect in disguise. Meaning that since the month of January is included in the winter months, the abnormal returns for January might be driving the Sell-in-May anomaly. On that being the case, Bouman & Jacobsen (2002) wanted to test the relationship between these calendar anomalies. As a consequence, another regression model was implemented to their testing framework. They introduced a second dummy variable to the regression in order to examine the January effect's influence on the Sell-in-May anomaly.

The objective behind the inclusion of a second dummy variable is to remove the January effect from the rest of the winter months and examine whether the Sell-in-May effect is statistically significant without it. This thesis has duplicated their regression model in order to investigate the influence of the January effect ourselves. Regression model (2) is illustrated below in equation 3.

$$R_t = \mu + \delta_1 SIM_t^{Adj} + \delta_2 Jan_t + \varepsilon_t \tag{3}$$

Where R_t is the return for the index, μ represents the intercept. δ_1 is the coefficient estimate for the Sell-in-May effect, SIM_t^{Adj} is the adjusted dummy variable for the Sell-in-May effect. δ_2 denotes the coefficient estimate for the January effect. Jan_t is the Dummy variable for the January effect, and ε_t is the constant error term.

To test the January effects impact on the Sell-in-May effect, the second dummy variable Jan_t was set to 1 in January and 0 in the subsequent months. Additionally, since both dummy variables cannot equal 1 in the same month, the Sell-in-May dummy must be adjusted for. As a consequence, The Sell-in-May dummy SIM_t^{Adj} therefore took the value of 0 in all January months. The coefficient estimate δ_1 indicates wether or not the Sell-in-May effect is absent when the January returns are excluded from the winter period.

By adding the second dummy variable, the coefficient estimate for the January effect, δ_2 is regressed. This coefficient will be considered in the same manner as to the Sell-in-May coefficient estimate. If the coefficient is positive and significant, we can draw to the conclusion that the index experiences a statistically significant January effect. Whereas δ_2 denotes the positive (or negative) excess return for January compared to subsequent months. Further, we applied the same significance thresholds as in equation 2 in order to examine the significance of the January effect, respectively 1, 5 and 10 percent.

It should be addressed that by adding a January dummy variable, it is expected that the new regression model is going to overestimate the January effect and to underestimate the Sell-in-May effect, according to Bouman & Jacobsen (2002). The authors argued that the new regression model will simply assume that the abnormal returns for January is solely due to the January effect, rather than the Sell-in-May effect, thus leading to underestimation of the Sell-in-May effect.

4.1.3 Capital Asset Pricing Model

Anomalies exist when patterns in average stock returns arise which cannot be addressed for by the CAPM (Fama & French, 2008). In order to enable the reader to adequately interpret the results presented in the empirical results section, we consider it important to provide some information on the CAPM. As the name suggests, the CAPM is a pricing model. The model has a variety of applications. The CAPM is used to determine the drivers of the equilibrium expected return on any risky asset in the market (Bodie et al., 2018). The model assumes that the expected excess return on a single risky asset is related to the market portfolio's expected excess return (Cuthbertson & Nitzche, 2004); however, in this thesis we will concentrate on the ones which are most relevant to our study. Especially the notions of alpha and beta must be accounted for. The most widely referenced equation for CAPM is illustrated below in equation 4.

$$R_t = \alpha + R_f + \beta_t \times (R_m - R_f) + \varepsilon_t \tag{4}$$

According to the CAPM, the return R_t on asset *t* equals the risk-free rate of interest, denoted as R_f , plus a risk premium. This risk premium is calculated by multiplying the risk premium per unit of risk, commonly referred to as the market risk premium, $(R_m - R_f)$, by the "beta" measure of how risky the asset *t* is (Sharpe, 1994). Beta cannot be observed in the market and must be estimated. Since it will not be possible to carry out any tests of the CAPM without knowing the beta, the first step is to estimate the beta coefficient (Brooks, 2019). Because the objective of our study is to examine the Sell-in-May effect, asset *t* equals the Sell-in-May portfolio. To estimate the beta, you take the covariance between the excess return on the asset *t* and the excess return on the market portfolio, and divide it by the variance of the market portfolio's excess return (Sharpe, 1994).

$$\beta_t = \frac{Cov(R_t, R_m)}{Var(R_m)} \tag{5}$$

It is vital to remember that the CAPM is an equilibrium model or a model in terms of expectation. As a result, we should not anticipate the CAPM to be applicable for every stock in every time period. However, it should hold on average, if it is a good model (Brooks, 2019). Typically, we will use a wide stock market index as a proxy for the market portfolio, and the risk-free rate normally equals the yield on short-term Treasury notes. In our case, we use each country's value-weighted MSCI reinvestment index as a market proxy, and long-term government bond yields with 10 years to maturity as a proxy for the risk-free rate.

In terms of our study, the objective behind the usage of the CAPM, is to examine the intercept estimate for the regression, namely the Jensen's alpha (α). This estimate coefficient indicates whether the asset *t* (Sell-in-May portfolio) under- or outperformed the market proxy, given its level of market risk (Sharpe, 1994). Since the alpha coefficient accounts for both risk and return, we are not interested in reporting and commenting on the beta coefficients. According to CAPM, if alpha is significantly different from zero, the security is mispriced. A positive significant alpha in our case would indicate that the Sell-in-May portfolio is outperforming the market index for the respective country. On the other hand, a negative significant alpha suggests that the Sell-in-May portfolio is underperforming the market (Ruppert, 2004).

The first CAPM was introduced by William Sharpe in 1964 and is a model that is based upon the portfolio theories of Markowitz from 1952 (Ross, 1978). The CAPM assumes that the only type of risk which can provide excess returns for stocks is market risk.

Fama & French (1993) later claimed that, in addition to market risk, market value risk, book-to-market ratio risk, profitability risk, and investment pattern risks also existed in the market. As a result, Fama & French developed the Fama-French 5-factor model, which accounted for these additional risk factors. For the model to capture and explain the market value effect, Fama & French added the factor Small minus Big (SMB) and High minus Low to explain the value effect. To explain the profitability effect, the factor Robust minus Weak profitability (RMW) was added. Lastly, for investment patterns, the factor Conservative minus Aggressive (CMA) was embroidered into the model.

In this thesis, we employ the Fama-French 5-factor model, with the objective to estimate corresponding alpha values for the Sell-in-May portfolio, and test if they are statistically significant. If we encompass positively significant alpha values, we can draw to the conclusion that the existence of the Sell-in-May effect cannot be explained for by the additional risk factors comprehended for in Fama-French 5-factor model. The 5-factor model is presented below in equation 6.

$$R_t - R_f = \alpha + \beta_t \times (R_m - R_f) + \beta_{SMB} \times SMB + \beta_{HML} \times HML + \beta_{RMW} \times RMW + \beta_{CMA} \times CMA + \varepsilon_t \quad (6)$$

4.1.4 Sharpe Ratio

Reward-to-volatility ratio, more commonly known as the Sharpe ratio, is a performance metric used to examine the risk-adjusted return of an investment (Sharpe, 1966). According to Sharpe (1966), the metric delivers the risk premium per unit of total risk. This risk premium is quantified by the investment's standard deviation of return (Sharpe, 1966). The Sharpe ratio uses the investment's average return in excess of the risk-free rate and divides it by the standard deviation derived from the same investment. Equation 7 presents the formula for the Sharpe ratio.

$$S_t = \frac{R_t - R_f}{\sigma_t} \quad (7)$$

4.2 Hypothesis Testing

To draw valid conclusions from our analyses of the Sell-in-May effect, we will need to run several hypothesis tests to check whether our findings are of statistical significance. First, we constructed two hypotheses for our regression models to test the statistical significance of the Sell-in-May effect in each country and index. Each hypothesis will consist of a null hypothesis (H_0) and an alternative hypothesis (H_A). It is important to note that hypothesis 1.1 addresses regression model (1), while hypothesis 1.2 deals with regression model (2). The objective of both hypotheses is to test whether the coefficient estimate δ_1 is equal to zero or not. If the estimated δ_1 is equal to zero the null hypothesis will not be rejected, indicating that the winter returns are not significantly higher than the summer returns. On the other hand, if δ_1 does not equal zero the alternative hypothesis will be accepted. Accepting the alternative hypothesis will provide evidence for an existing Sell-in-May effect in the market.

Further, we construct four additional hypotheses. Hypotheses 2 and 3 tests for the difference in mean return between the summer and winter period, and the difference in standard deviation between the same two periods. Hypothesis 4 examine if Jensen's alpha from CAPM and alpha from Fama-French 5-factor model in the Sell-in-May strategy is significantly different from zero. A positive significant alpha estimate indicates that the Sell-in-May portfolio is beating the market proxy given its level of risk. The final hypothesis, hypothesis 5, test whether the Sharpe ratio for the Sell-in-May and Buy-and-Hold strategies are statistically different from one another.

$H_0 : \delta_1 = 0$

$H_A : \delta_1 \neq 0$

1.1. Is the Sell-in-May effect for the market statistically significant?

1.2. Is the Sell-in-May effect for the market statistically significant when the January effect is included?

$$t = \frac{\delta_1}{se(\delta_1)}$$

To test the statistical significance of δ_1, a T-test was applied. δ_1 denotes the coefficient estimate, while $se(\delta_1)$ is the corresponding standard error for this coefficient estimate.

H$_0$: $m_W = m_S$

H$_A$: $m_W \neq m_S$

2. Is the mean return for the winter period statistically different from the summer period?

$$t = \frac{m_W - m_S}{\sqrt{\frac{S_W^2}{n_W} + \frac{S_S^2}{n_S}}}$$

To test this hypothesis, we used Welch's (1938, 1947, 1951) two-sample T-test for equal means when the population variances are unequal. The test statistics for the equal mean test is presented above. m_W refers to the mean return for the winter period, while m_S refers to the mean return for the summer period. S_W^2 and S_S^2 represents the variance for the winter and summer periode, while n_W and n_S represents the size of the winter and summer period.

H$_0$: $\sigma_W = \sigma_S$

H$_A$: $\sigma_W \neq \sigma_S$

3. Is the standard deviation for the winter period statistically different from the summer period?

$$f = \frac{S_W^2}{S_S^2}$$

To test for equality of two variances, we used a two-tailed F-test. The formula above is the test statistic used to test for equal variance between two periods (Snedecor & Cochran, 1989), where S_W^2 and S_S^2 represents the variance for the winter and summer period.

$H_0 : \alpha = 0$

$H_A : \alpha \neq 0$

4. Is alpha for the Sell-in-May strategy statistically different from zero in the Capital Asset Pricing Model and the Fama-French 5-factor model?

$$t = \frac{\alpha}{se(\alpha)}$$

To test the significance of α, a T-test was applied. α denotes the coefficient estimate, while $se(\alpha)$ is the corresponding standard error for this coefficient estimate.

$H_0 : S_{SIM} = S_{B\&H}$

$H_A : S_{SIM} \neq S_{B\&H}$

5. Is the Sharpe ratio for the Sell-in-May strategy statistically different from the Buy-and-Hold strategy's Sharpe ratio?

$$z = \frac{S_{SIM} - S_{B\&H}}{\sqrt{\frac{1}{T}[2(1-p) + \frac{1}{2}(S_{SIM}^2 + S_{B\&H}^2 - 2p^2 S_{SIM} S_{B\&H})}}$$

The formula above illustrates the test statistic for the Sharpe ratio test (Jobson & Korkie, 1981). S_{SIM} denotes the estimated Sharpe ratio for the Sell-in-May strategy, $S_{B\&H}$ is the Sharpe ratio for the Buy-and-Hold strategy, whereas p represents the correlation coefficient between the returns for both strategies over a sample of T months. z is asymptotically standard normal under the null hypothesis.

4.3 Heteroscedasticity and Autocorrelation

In order for our estimation technique, ordinary least square (OLS) to be BLUE (Best Linear Unbiased Estimator), the theory from the classical linear regression model (CLRM) proposes five restrictive assumptions on the residuals that should be met (Brooks, 2019). Since the error term is a population value that will never be known, we use the residuals instead as they are the sample estimate of the error for each observation.

The first assumption that must be satisfied is that the average value of errors is zero. Since we have included a constant term in the regression equation, this first assumption will never be violated. The second criterion is called "the assumption of homoscedasticity" and assumes that the variance of errors is constant. If the variance of errors is not constant, they are assumed to be heteroscedastic. The third assumption states that the covariance between the error terms must be zero over time. Meaning that errors are assumed to be uncorrelated with each other. If the errors are not uncorrelated, errors are thought to be autocorrelated or serially correlated. The fourth assumption assumes that OLS is consistent and unbiased in presence of stochastic regressors, assuming that the regressors are uncorrelated to the estimated error term. The fifth assumption assumes that the error term is normally distributed (Brooks, 2019). In practice, all assumptions are rarely met.

To test whether the second assumption was met or not, we conducted the Breusch-Pagan test on the corresponding residuals from both regression models to check for heteroscedasticity. The presence of heteroscedasticity indicates that the variance is nonconstant.

Furthermore, The Breusch-Godfrey test was applied to residuals in both regression models, to test if the third assumption is met. The Breusch-Godfrey test indicates whether a dataset in a linear regression contains autocorrelation or not. According to Breusch & Godfrey (1978), autocorrelation exists when errors are due to previous errors and hence correlated over time.

When the issue of autocorrelation and heteroscedasticity occurs, the standard errors of estimation of parameters in an OLS must be computed correctly. To correct these errors, we have applied the Newey-West estimator, which corrects for both autocorrelation and heteroscedasticity (Newey & West, 1987). When we conducted the Breusch-Godfrey test and the Breusch-Pagan test, we observed that the residuals in both regression models for some countries and indices contained autocorrelation as well as heteroscedasticity. As a result, we applied the Newey-West estimator for all countries and indices to compute errors correctly for both autocorrelation and heteroscedasticity in both regression models. Correcting these errors provides reliability to the regression models used in this thesis.

The second and third assumptions are tested in the hypotheses below: the first hypothesis looks at whether the standard errors in the regression model are heteroscedastic, and the second determines if the regression's standard errors are autocorrelated or not.

H_0 : Homoscedasticity is present

H_A: Heteroscedasticity is present

Is heteroscedasticity present in the regression model or not?

H_0: There is no autocorrelation at any order less or equal to p (p = 12)

H_A: There exists autocorrelation at some order less than or equal to p (p = 12)

Are the standard errors in the regression model autocorrelated or not?

Table 1: Breusch-Pagan Test for Heteroscedasticity

			Regression Model 1		Regression Model 2	
Country	Period	Observations	Test Statistics	p-Values	Test Statistics	p-Values
SP500(1)	1870-1920	601	8.50	0.004	8.93	0.01
SP500(2)	1920-1970	601	1.95	0.16	2.82	0.24
SP500(3)	1970-2020	601	2.21	0.14	5.05	0.08
DJIA(1)	1896-1936	487	1.40	0.24	3.59	0.17
DJIA(2)	1936-1976	492	0.20	0.65	0.49	0.78
DJIA(3)	1976-2020	540	1.44	0.23	3.78	0.15
Australia	1975-2020	552	1.12	0.29	1.33	0.51
Austria	1990-2020	372	1.32	0.25	1.39	0.50
Belgium	1975-2020	552	0.04	0.84	0.11	0.95
Canada	1977-2020	528	0.84	0.36	0.89	0.64
Denmark	1989-2020	384	2.61	0.11	2.62	0.27
France	1975-2020	552	0.46	0.50	2.26	0.32
Germany	1975-2020	552	1.53	0.22	1.87	0.39
Ireland	1991-2020	360	0.04	0.85	0.30	0.86
Italy	1991-2020	360	0.39	0.53	0.42	0.81
Japan	1989-2020	384	0.15	0.70	0.17	0.92
Netherlands	1975-2020	552	1.80	0.18	2.70	0.26
Norway	1985-2020	432	1.64	0.20	1.75	0.42
Spain	1980-2020	492	0.99	0.32	1.18	0.55
Sweden	1987-2020	408	0.67	0.41	0.77	0.68
Switzerland	1975-2020	552	0.58	0.45	2.15	0.34
UK	1975-2020	552	0.35	0.55	0.59	0.74

Notes: H_0 : Homoscedasticity is present , H_A: Heteroscedasticity is present . P-value < 0.05 → reject H_0. P-value > 0.05 → fail to reject H_0. SP500(1) and DJIA(1) refers to sub-period 1, SP500(2) and DJIA(2) refers to sub-period 2, and SP500(3) and DJIA(3) refers to sub-period 3.

Table 2: Breusch-Godfrey Test for Autocorrelation

	Regression Model 1		Regression Model 2	
Country	Test Statistics	p-Values	Test Statistics	p-Values
SP500(1)	4.06	0.25	4.17	0.24
SP500(2)	31.98	0.001	32.83	0.001
SP500(3)	12.90	0.38	12.88	0.38
DJIA(1)	31.87	0.001	32.46	0.001
DJIA(2)	17.53	0.13	17.72	0.12
DJIA(3)	8.09	0.78	7.49	0.82
Australia	3.49	0.32	3.55	0.31
Austria	8.52	0.036	8.88	0.03
Belgium	9.73	0.02	10.62	0.01
Canada	1.47	0.69	1.47	0.69
Denmark	11.93	0.45	11.98	0.45
France	13.59	0.33	14.91	0.25
Germany	7.84	0.80	8.46	0.75
Ireland	15.06	0.24	15.04	0.24
Italy	10.29	0.59	10.35	0.59
Japan	16.11	0.19	17.06	0.15
Netherlands	7.06	0.85	6.86	0.87
Norway	6.06	0.11	6.24	0.10
Spain	11.77	0.46	12.25	0.43
Sweden	14.99	0.24	16.14	0.18
Switzerland	13.32	0.35	14.02	0.30
UK	9.16	0.69	12.03	0.44

Notes: H_0: There is no autocorrelation at any order less or equal to p. H_A: There exists autocorrelation at some order less than or equal to p. P-value < 0.05→ Reject H_0. P-value > 0.05 → Fail to reject H_0 Order p = 12.

5 Empirical Results

In this chapter, the empirical results from our analysis will be described and presented. Firstly, we introduce the results on whether the Sell-in-May effect is statistically significant for the various international countries and indices examined. As stated in the methodology section, we have applied two Ordinary Least Square regressions, testing the Sell-in-May effect with and without accounting for the January effect. Secondly, similarly to Bouman & Jacobsen's (2002) study, we further present a table containing each country's average monthly returns. To illustrate the magnitude of the Sell-in-May effect, we have constructed a bar chart that displays the difference in market return between the summer and winter periods for various international countries. Furthermore, in table 5, we make comparisons between the summer and winter periods in terms of mean return and standard deviation.

Next, we construct and simulate the Sell-in-May effect into a trading strategy to examine whether or not investors can exploit and profit from the anomaly. First, we compare Sharpe ratios for the Sell-in-May strategy and from a Buy-and-Hold perspective. Then, by applying the Capital Asset Pricing Model we first test whether Jensen's alpha for the Sell-in-May strategy is positive and statistically different from zero or not. Furthermore, we introduce alpha estimates calculated from the Fama-French 5-factor model, with the respective significance levels. Alpha values from both CAPM and the Fama-French 5-factor model are presented simultaneously in table 7. Finally, we plot the cumulative returns for each strategy, intending to get a better grasp of the overall performance of the investment strategies.

5.1 Time-series Regression

As illustrated in table 3, for both the S&P 500 and DJIA indices, only the third sub-period experiences a statistically significant relationship between the Sell-in-May dummy and the mean return in both model specifications. For sub-period 1 and 2 however, our regression models do not demonstrate any significant Sell-in-May effect on the S&P 500 or the DJIA index on any level of significance. Indicating that the Sell-in-May effect has not been very noticeable in those specific time periods.

Without accounting for the January effect, 15 out of 16 international countries experience a statistically significant relationship (at the 10% level) between the Sell-in-May dummy and the country's mean return, the only exception being Japan. By accounting for the January effect, we now observe that 14 international countries exhibit a statistically significant relationship between the adjusted Sell-in-May dummy and the mean return. Interestingly, the distribution of significance slightly fluctuates for some international countries. For instance, after correcting for the January effect, the t-value for the Sell-in-May dummy in Australia turns insignificant, whilst the corresponding t-values of Switzerland advance from being significant at a 5% level to being significant at the 1% level. For all other international countries, the Sell-in-May effect remains significant at their respective significance levels. This result indicates that the January effect is not a valid explanation for the existence of a Sell-in-May effect.

If we take a look at the t-values for the January dummy in the right column, we observe that the UK is the only country with a statistically significant January dummy. For the remaining samples, no international countries or any US indices experience a statistically significant January dummy.

Table 3: Summary Statistics and Sell-in-May Effect

Country	Mean Return	Standard Deviation	Reg (1) δ_1	t-Values of Sell in May Dummy (No January Effect)	Reg (2) δ_1	t-Values of Adjusted Sell in May Dummy with January Effect	Reg (2) δ_2	t-Values of January Dummy with Adjusted Sell in May Dummy
SP500(1)	0.55	4.16	0.21	0.58	0.07	0.20	0.86	1.52
SP500(2)	0.79	6.06	0.01	0.004	-0.11	-0.24	0.59	0.85
SP500(3)	0.83	4.36	0.87	**2.67*** **	0.88	**2.68*** **	0.82	1.14
DJIA(1)	0.74	6.90	0.14	0.24	0.004	0.007	0.82	1.01
DJIA(2)	0.76	4.45	0.33	0.80	0.24	0.61	0.74	0.91
DJIA(3)	0.92	4.33	1.04	**3.30*** **	1.11	**3.40*** **	0.68	0.99
Australia	0.88	6.92	0.81	**1.70* **	0.89	1.48	0.78	0.81
Austria	0.46	6.88	1.92	**2.96*** **	2.00	**2.92*** **	1.56	1.41
Belgium	0.92	5.63	1.69	**3.67*** **	1.91	**4.11*** **	0.60	0.72
Canada	0.76	5.67	0.98	**2.17** **	1.11	**2.34** **	0.30	0.35
Denmark	0.93	5.49	1.09	**2.34** **	1.05	**2.10** **	1.29	1.38
France	0.89	6.38	1.70	**3.60*** **	1.93	**3.95*** **	0.54	0.61
Germany	0.82	6.02	1.19	**2.76*** **	1.56	**3.40*** **	-0.65	-0.79
Ireland	0.53	6.77	1.67	**2.91*** **	1.75	**2.95*** **	1.26	1.10
Italy	0.41	6.93	2.06	**3.47*** **	2.06	**3.28*** **	2.04	1.53
Japan	0.14	5.69	0.41	0.74	0.58	0.96	-0.36	-0.37
Netherlands	1.07	5.50	1.52	**3.77*** **	1.74	**4.05*** **	0.42	0.57
Norway	0.85	7.50	1.75	**2.53** **	1.81	**2.57** **	1.41	1.13
Spain	0.82	6.63	1.29	**2.35** **	1.26	**2.17** **	1.40	1.29
Sweden	0.92	6.95	1.98	**3.47*** **	2.14	**3.29*** **	1.15	0.99
Switzerland	0.94	4.92	0.69	**2.13** **	0.93	**2.73*** **	-0.50	-0.70
UK	0.96	5.93	1.80	**3.60*** **	1.83	**3.76*** **	1.66	**1.95* **

Notes: T-values and corresponding p-values: 1.65*; 1.96**; 2.58***, p<0.1*; p<0.05**; p<0.01***. The monthly mean returns and standard deviations are presented as percentages. Reg (1) δ_1 is the coefficient estimate from the first regression model (equation 2) and is presented as a percentage, Reg(2) δ_1 is the first coefficient estimate from the second regression model (equation 3), Reg(2) δ_2 is the second coefficient estimate from the second regression model (equation 3). The t-values for the Sell-in-May dummy with no January effect, for the adjusted Sell-in-May dummy with January effect, and for the January dummy with the adjusted Sell-in-May dummy, are presented in columns, 5, 7, and 9. Newey-West errors were computed.

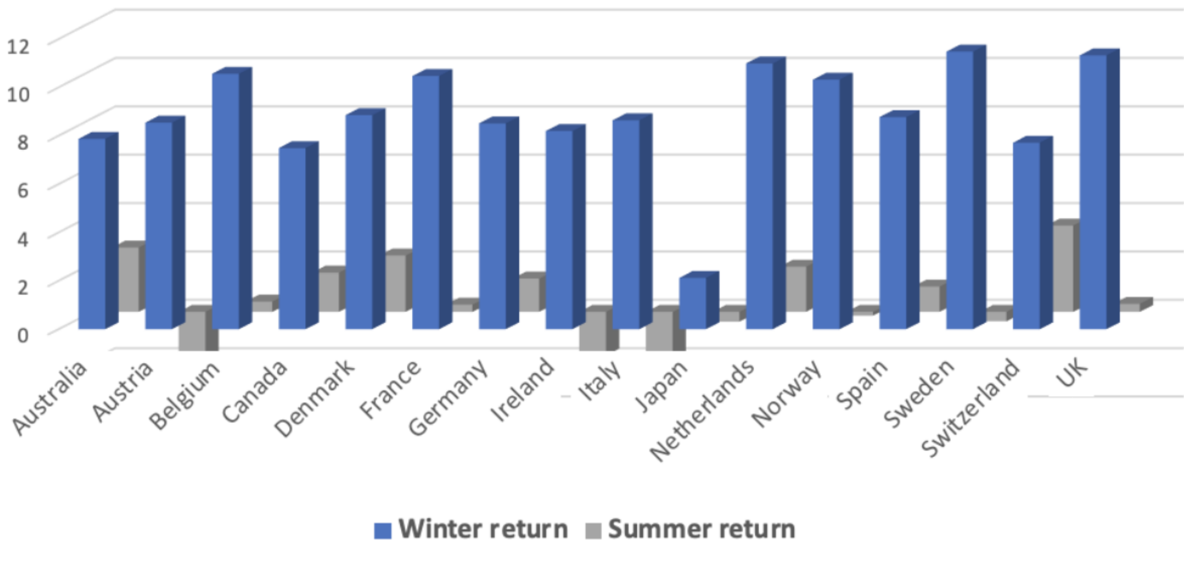
The question of whether the low returns from May to November are more or less evenly distributed over these months, or whether they are linked to certain months, is an intriguing one. Table 4 below illustrates the monthly average returns for all international countries and sub-periods employed in our study. Furthermore, figure 1 illustrates the difference in returns between the summer and winter period for the international countries.

Table 4: Average Monthly Returns

Country	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
SP500(1)	1.37	-0.37	0.84	0.92	-0.13	-0.08	0.63	1.70	0.19	0.34	0.60	0.61
SP500(2)	1.56	-0.10	0.14	1.27	-0.33	1.17	2.84	1.76	-0.96	0.25	0.46	1.62
SP500(3)	1.34	0.59	1.37	1.53	0.60	0.56	0.87	0.26	-0.34	1.06	1.57	1.74
DJIA(1)	0.59	1.46	3.78	-1.85	0.08	1.33	0.33	1.49	-0.32	1.51	0.50	-0.06
DJIA(2)	1.34	0.31	0.44	1.01	-0.12	0.77	1.83	0.03	0.04	1.06	0.24	2.22
DJIA(3)	1.08	0.60	1.22	2.28	0.53	0.32	1.43	-0.07	-0.50	0.52	2.03	1.57
Australia	1.22	-0.18	0.47	3.46	0.3	-0.08	2.02	0.58	0.18	-0.36	0.01	2.88
Austria	1.06	1.79	0.09	2.11	-0.18	-0.05	1.19	-1.41	-1.87	-0.67	0.01	3.41
Belgium	0.67	1.36	0.91	2.76	-1.31	0.27	1.84	-0.14	0.25	-0.49	1.24	3.60
Canada	0.57	0.70	0.61	2.01	1.31	0.26	1.03	0.68	-0.98	-0.67	1.75	1.84
Denmark	1.67	0.68	0.63	2.06	1.19	0.32	2.85	-1.30	-0.65	-0.07	0.41	3.39
France	0.58	1.33	1.34	3.19	-0.67	-0.79	1.03	0.32	-0.14	0.55	1.40	2.63
Germany	-0.42	0.99	0.98	2.43	-0.99	0.82	1.36	-0.93	-0.34	1.46	1.41	3.14
Ireland	0.96	1.51	0.68	1.84	-0.59	-1.3	-0.14	0.47	0.14	-0.39	0.55	2.65
Italy	0.06	3.93	-0.96	-1.45	0.95	-1.09	-1.05	-0.10	0.83	3.26	1.42	-0.94
Japan	-0.43	-0.31	0.11	2.07	0.09	0.06	0.38	-0.89	-0.20	0.15	-0.33	1.00
Netherlands	0.74	0.68	2.08	2.69	-0.45	0.68	1.71	-0.02	-0.64	0.59	1.53	3.26
Norway	1.39	1.09	1.31	4.02	-0.03	-0.40	2.62	-0.96	-0.62	-0.76	-0.60	3.10
Spain	1.58	1.21	0.33	2.18	-0.06	0.07	1.14	-0.32	-0.22	0.43	1.69	1.80
Sweden	1.09	2.13	0.30	3.84	0.09	-0.40	2.58	-1.72	-0.72	-0.21	1.18	2.95
Switzerland	0.09	0.26	0.94	1.85	0.14	0.98	1.43	0.03	0.28	0.71	1.29	3.28
UK	1.72	0.97	0.54	3.73	-0.55	-0.68	1.54	0.62	-0.86	0.27	1.28	2.91

Notes: Mean returns for each specific month for every index and country, reported as percentages.

Figure 1: Mean returns Summer and Winter



Notes: Semi-annualized mean returns from May-October (Summer) and November-April (Winter) for all 16 examined international countries, presented as percentages.

5.2 Risk-Return Relationship

A question that needs to be considered regarding the Sell-in-May effect, is whether the risk in terms of volatility can be a natural explanation for the existence of the effect. If the winter period's abnormal returns are accompanied by a higher level of risk, we could argue that risk is one possible explanation for the Sell-in-May effect. In table 5 we present the mean return and standard deviation for the winter and summer periods. Mean returns and standard deviations are calculated semi-annually. On top of that, we have conducted Welch's two-sample test on equal means and an F-test for equality of two variances to ensure that the mean returns and standard deviations for the two periods are significantly distinctive. If the corresponding p-values are less than the threshold value of 0.1, mean returns or standard deviations are significantly different from one another. In column 6 in the table below, we observe that the majority of countries and indices have significantly different means, while in column 7 the standard deviations are only significantly distinctive in 10 out of 22 countries and indices examined.

If we take a closer look at table 5, we observe that the period from November to April generates a higher mean return compared to May to October in all indices and countries. Interestingly, we notice only a marginal difference in the standard deviation between the two periods. In most international countries, the summer months actually generate a higher standard deviation despite the lower returns. There are only two exceptions.

For Italy and Ireland, the standard deviation for the winter months is higher compared to the summer months. The difference here is also marginal, with 0.93% for Italy and 0.34% for Ireland. Arguing that higher risk contributes to higher returns in the winter months is unlikely according to the results presented in table 5. For the two exceptions observed in the Italian- and the Irish market, an increase in the risk premium of more than 10% would be required to compensate for a 0.93% (Italy) and 0.34% (Ireland) increase in the standard deviation.

Table 5: Returns and Standard Deviations

	November to April		May to October			
Country	Mean Return	Standard Deviation	Mean Return	Standard Deviation	p-Values$_{MR}$	p-Values$_{SD}$
SP500(1)	3.95	9.02	2.65	11.27	0.66	**0.0001*** **
SP500(2)	4.96	13.41	4.73	16.13	0.99	**0.002*** **
SP500(3)	7.59	9.93	2.39	11.31	**0.022** **	**0.023** **
DJIA(1)	4.84	15.76	4.01	17.98	0.83	**0.04* **
DJIA(2)	5.56	10.61	3.60	11.22	0.42	0.38
DJIA(3)	8.78	10.20	2.24	10.89	**0.005*** **	0.29
Australia	7.87	15.56	2.66	18.29	0.14	**0.005*** **
Austria	8.54	15.31	-3.00	17.97	**0.007*** **	**0.03** **
Belgium	10.56	13.51	0.43	13.80	**0.0004*** **	0.72
Canada	7.49	13.13	1.62	14.49	**0.05** **	0.11
Denmark	8.85	12.17	2.33	14.55	**0.053* **	**0.014** **
France	10.47	15.06	0.30	15.92	**0.002*** **	0.36
Germany	8.51	13.93	1.38	15.40	**0.02** **	**0.1* **
Ireland	8.20	16.63	-1.81	16.29	**0.02** **	0.78
Italy	8.64	17.26	-3.70	16.33	**0.005*** **	0.46
Japan	2.12	13.69	-0.41	14.18	0.47	0.63
Netherlands	10.99	12.48	1.87	14.18	**0.001*** **	**0.03** **
Norway	10.32	16.89	-0.16	19.52	**0.015** **	**0.03** **
Spain	8.77	15.62	1.05	16.68	**0.03** **	0.31
Sweden	11.48	16.02	-0.40	17.68	**0.004*** **	0.16
Switzerland	7.71	11.56	3.57	12.46	**0.099* **	0.22
UK	11.33	14.57	0.33	14.16	**0.0003*** **	0.63

Notes: $p<0.1$*; $p<0.05$**; $p<0.01$***. Semi-annually mean returns and standard deviations from May-October (Summer) and November-April (Winter) for all countries and indices, presented as percentages. P-values from Welch's two-sample test from testing statistical differences in mean returns. p-Values$_{MR}$ indicates the p-values for the mean return test, p-Values$_{SD}$ indicates the p-values for the equal variance test.

5.3 Sell-in-May Strategy versus Buy-and-Hold Strategy

In this section, we compare and analyze the performance between two investment strategies. The two investment strategies that were tested were a Sell-in-May strategy and a passive Buy-and-Hold strategy. The Sell-in-May strategy clearly separates itself from the Buy-and-Hold strategy, by being a market timing strategy. With this strategy/approach, the investor tries to exploit the Sell-in-May anomaly by holding a market portfolio in the winter period and then switches to holding a risk-free asset over the summer period, such as long-term government bonds. Whilst the Buy-and-Hold strategy constantly holds on to the same portfolio composition, namely the market portfolio. To compare the two strategies, the Sharpe ratio and Jensen's alpha will be applied. Finally, to account for additional risk factors, we have computed alpha estimates from the Fama-French 5-factor model as well.

Table 6 represents the annualized mean return, standard deviation, and Sharpe ratio for the Sell-in-May strategy and the Buy-and-Hold strategy. To examine the absolute risk-adjusted performance of the two strategies, we have computed annual Sharpe ratios and tested whether they are statistically different from each other by drawing conclusions based on z-statistics and p-values. For the US indices, none of the Sharpe ratios computed are statistically different from one another on any level of significance. However, 10 out of 16 international countries experienced a statistically significant difference in the Sharpe ratio between the strategies. Three were significant at the 10% level, five at the 5% level, and two at the 1% level. For the US indices, all sub-periods were statistically insignificant.

Table 6: Sell-in-May versus Buy-and-Hold

Country	Mean Return Sell-in-May	Mean Return Buy-and-Hold	Standard Deviation Sell-in-May	Standard Deviation Buy-and-Hold	Sharpe Sell-in-May	Sharpe Buy-and-Hold	p-Values
SP500(1)	5.93	6.60	9.04	14.42	0.21	0.17	0.80
SP500(2)	6.00	9.69	13.45	20.96	0.28	0.35	0.54
SP500(3)	9.92	9.99	10.06	15.11	0.52	0.35	0.17
DJIA(1)	6.40	8.83	15.70	23.90	0.21	0.24	0.81
DJIA(2)	6.81	9.16	10.67	15.43	0.42	0.42	0.85
DJIA(3)	10.80	11.03	10.38	15.01	0.62	0.45	0.18
Australia	11.78	10.53	15.50	23.97	-0.14	0.10	0.29
Austria	10.58	5.55	15.42	23.83	0.42	0.07	**0.03****
Belgium	13.66	10.98	13.68	19.51	0.55	0.24	**0.02****
Canada	10.77	9.12	13.20	19.64	0.35	0.14	0.16
Denmark	11.05	11.18	12.32	19.04	0.55	0.35	0.27
France	13.78	10.77	15.22	22.10	0.48	0.17	**0.02****
Germany	11.03	9.89	14.04	20.86	0.42	0.24	0.12
Ireland	10.57	6.38	16.71	23.43	0.35	0.07	**0.06***
Italy	11.35	4.87	17.28	23.99	0.35	-0.03	**0.01*****
Japan	3.12	1.72	13.7	19.72	0.07	-0.01	0.48
Netherlands	13.69	12.85	12.71	19.06	0.66	0.38	**0.05****
Norway	13.24	10.16	17.03	25.97	0.45	0.17	**0.07***
Spain	12.60	9.82	15.72	22.95	0.31	0.10	**0.08***
Sweden	14.09	11.09	16.24	24.09	0.55	0.24	**0.04****
Switzerland	9.32	11.20	11.70	17.03	0.51	0.48	0.69
UK	14.68	11.46	14.75	20.55	0.52	0.21	**0.01*****

Notes: $p<0.1$*; $p<0.05$**; $p<0.01$***. Annualized mean returns and standard deviations from the Sell-in-May and Buy-and-Hold strategies, presented as percentages. Annualized Sharpe ratio from the Sell-in-May and Buy-and-Hold strategies with corresponding p-values to check for statistical significance in the differences in Sharpe ratios.

In table 7, the estimation results from the CAPM and the Fama-French 5-factor model are presented. For all international countries and US indices, we observe positive Jensen's alpha estimations from the CAPM. As mentioned earlier, a statistically significant positive alpha coefficient indicates that the Sell-in-May strategy outperforms the (market portfolio) Buy-and-Hold strategy given its level of market risk. However, in our case, not all alpha estimates are significantly different from zero. By using a significance level of 10%, 14 international countries experience a positive statistically significant alpha value. Australia and Japan are the only exceptions. Further, when we increase the significance level to 5%, Switzerland is the only country turning insignificant.

Interestingly, if we take a look at the different sub-periods for the US indices, we experience similar results as in the time series regression. For both S&P 500 and DJIA, only sub-period 3 experiences a statistically significant alpha value. Whilst sub-period 1 and 2 encountered insignificant alpha coefficients for both US indices.

Since the beta coefficient from the CAPM is a measure that only accounts for the systematic risk, we wanted to test the Sell-in-May effect by including additional risk factors. The Jensen's alpha coefficients are estimated through the single-factor model (CAPM), meaning that the market excess return is the single factor accounted for.

To see whether the abnormal returns for the winter period still exist after accounting for more risk factors, we have computed new alpha estimates through a multifactor model. The new model we have applied is commonly known as the Fama-French 5-factor model. In addition to the market excess return, this model also captures the risk factors of size, value, profitability, and investment patterns in the average stock returns. On the right-hand side of table 7, we present alpha estimates from the Fama-French 5-factor model, in addition to their respective significance levels measured in p-values.

By accounting for these additional risk factors, 8 out of 16 international countries experienced a significant alpha value from the 5-factor model. 5 countries are significant at a 10% level, and 3 countries at a 5% level. For both the US indices, sub-period 3 experienced statistically significant alpha values on a 1% level. These results show that by accounting for the additional risk factors, every alpha value is positive, however, the number of significantly positive alpha estimations decreases compared to Jensen's alpha estimations in the single index model. We can conclude that for DJIA and S&P 500 in sub-period 3 and half of the international countries examined, the abnormal returns cannot be explained by the known risk factors.

Table 7: CAPM and Fama-French 5-Factor Estimations

Country	CAPM α	p-Values	FF5 α	p-Values
SP500(1)	0.07	0.39	No data	No data
SP500(2)	0.06	0.60	No data	No data
SP500(3)	0.23	**0.004*** **	2.00	**0.007*** **
DJIA(1)	0.07	0.65	No data	No data
DJIA(2)	0.10	0.36	No data	No data
DJIA(3)	0.29	**0.0006*** **	0.28	**0.002*** **
Australia	0.24	0.12	0.23	0.23
Austria	0.49	**0.006*** **	0.41	**0.02** **
Belgium	0.42	**0.002*** **	2.23	0.13
Canada	0.26	**0.05** **	2.06	0.26
Denmark	0.32	**0.03** **	0.29	**0.02** **
France	0.43	**0.0004*** **	0.30	**0.04** **
Germany	0.32	**0.009*** **	0.32	**0.04** **
Ireland	0.30	**0.009*** **	0.37	**0.014** **
Italy	0.52	**0.003*** **	0.40	**0.02** **
Japan	0.11	0.50	0.16	0.23
Netherlands	0.42	**0.0005*** **	0.30	**0.03** **
Norway	0.46	**0.011** **	0.28	0.15
Spain	0.33	**0.03** **	0.26	0.14
Sweden	0.52	**0.005*** **	0.57	**0.003*** **
Switzerland	0.19	**0.06* **	0.18	0.11
UK	0.45	**0.001*** **	0.16	0.21

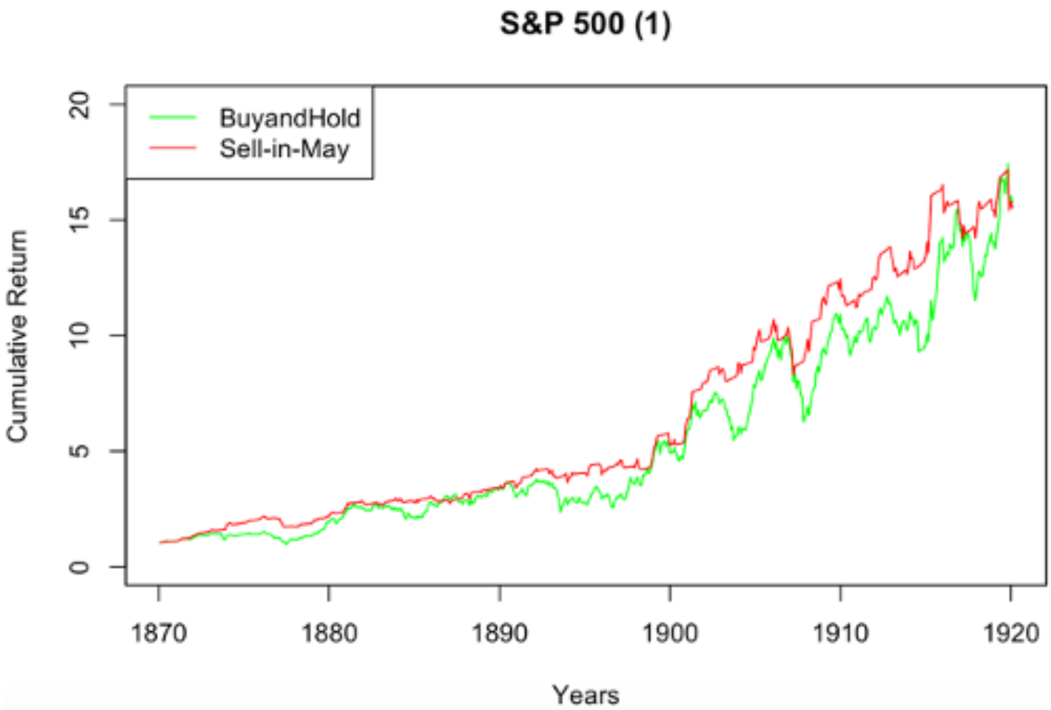
Notes: p<0.1*, p<0.05**, p<0.01***. α coefficient estimates from the CAPM and the Fama-French 5-factor model with corresponding p-values to check statistical significance. Newey-West errors were computed.

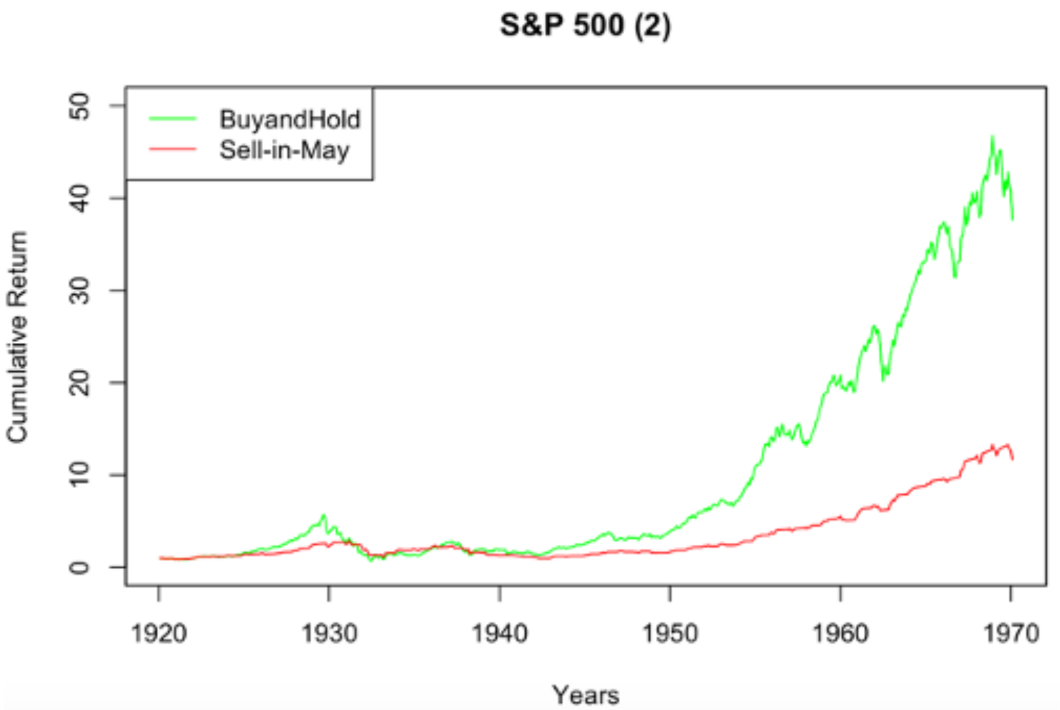
To get a visualization of the overall performance of the two strategies, the cumulative return for each country was plotted. The cumulative return represents the total return generated by each specific investment strategy. Figure 2 presents the cumulative returns for the three different sub-periods based on the S&P 500 index. For the first period, we see that the two strategies move similarly. The Sell-in-May strategy generates approximately the same amount of return as the Buy-and-Hold strategy in this time period.

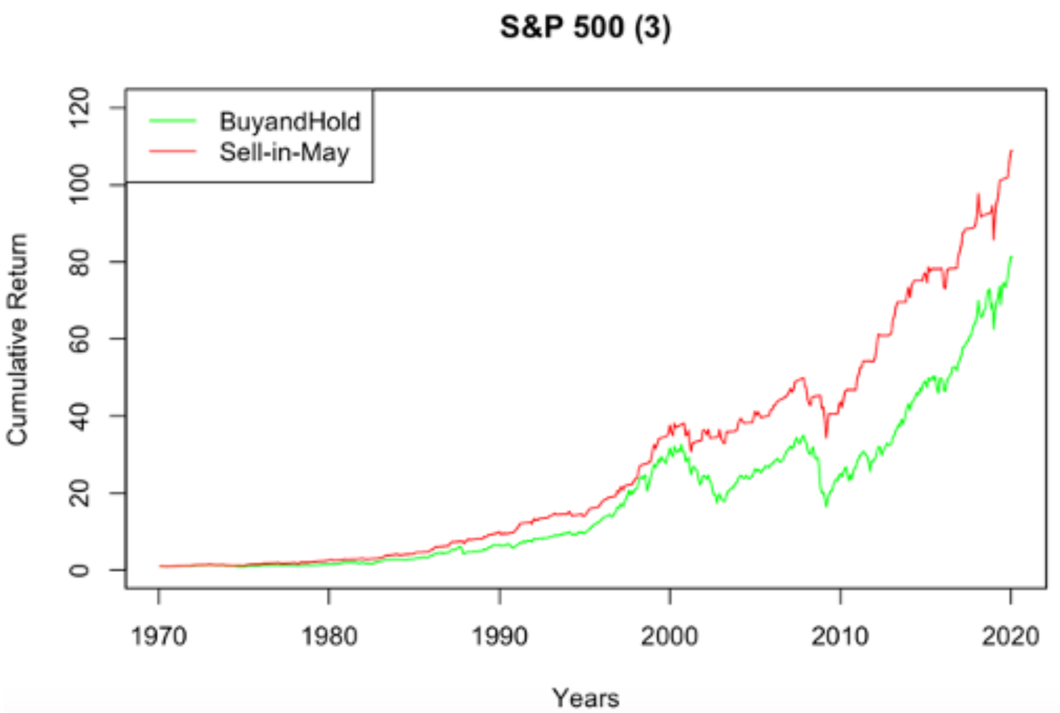
In sub-period 2, the figure shows that the Sell-in-May strategy falls short of generating the same amount of return as the Buy-and-Hold strategy. This changes in the last sub-period. Overall, for this period we see that the Sell-in-May strategy has generated a higher total amount of return compared to the Buy-and-Hold strategy.

Appendix A1 contains the cumulative return plots for the DJIA index. We should note that the cumulative returns for this index follow the same pattern as the S&P 500. In Appendix A2, we also present the cumulative return for all international countries. An interesting observation here is that almost all of the international countries provide the same results as sub-period 3 for both the S&P 500 and the DJIA. Switzerland is the sole exception. Switzerland is the only country where the Buy-and-Hold strategy generates a higher total amount of return compared to the Sell-in-May strategy.

Figure 2: Cumulative Returns for S&P 500







Notes: Cumulative returns for S&P 500 for all three sub-periods

6. Discussion and Interpretation

In this chapter, we will interpret and discuss our empirical findings, which were presented in the previous chapter. Firstly, the section starts by comparing our results from the time series regression with findings from existing academic studies on the topic. We will discuss the number of sub-periods and international countries that experiences a significant Sell-in-May effect, compare the strength of the effect through t-values, and additionally investigate how much the January effect coincides with the Sell-in-May effect for the various international countries examined. Further, we discuss differences in mean return and standard deviation between the summer and winter period. Additionally, we exchange views on the risk-return relationship between the Sell-in-May strategy and the Buy-and-Hold strategy. We do so by examining Sharpe ratios, Jensen's alpha from the Capital Asset Pricing Model, and alpha estimates from the Fama-French 5-factor model.

By examining the two US stock market indices, namely the S&P 500 and DJIA, results from the regression model indicated no evidence of any significant Sell-in-May effect for either sub-period 1 or 2, with and without accounting for the January effect. Although we experienced a positive δ_1 coefficient for all sub-periods, the results regarding subperiod 1 and 2 are not robust enough. For subperiod 3 however, both S&P 500 and DJIA experienced a statistically significant Sell-in-May effect, as the δ_1 coefficient was significantly different from zero on the 1% level. As stated in the problem formulation, we wanted to test different sub-periods in order to observe how the strength of the Sell-in-May effect has deviated through time. The findings clearly indicate that the effect has been more present in recent history, specifically between 1970 and 2020, compared to 1870 to 1920, and 1920 to 1970. By breaking their data sample from 1926 to 2008 into 3 equally long sub-periods, Haggard & Witte (2010), finds no evidence for a Sell-in-May effect in the earliest subperiod. This finding is remarkably similar to both ours and Lucey & Shao's (2008) scientific work. Furthermore, Haggard & Witte (2010) discovered a Sell-in-May effect that is significant and independent of the January effect over the last 55 years. Although the timeframe between our studies differs slightly, this finding corresponds to our discovery for sub-period 3.

Without accounting for the January effect, our regression model revealed that 15 out of 16 international countries experienced a statistically significant Sell-in-May effect on the 10% level, with Japan being the only exception. In other words, 15 out of 16 international countries encountered a positive δ_1 coefficient that was significantly different from zero, indicating that it is highly unlikely that the positive δ_1 coefficient is caused by randomness. Bouman & Jacobsen (2002) found a significant Sell-in-May effect in 20 out of 37 countries. By comparing the same 16 countries examined in our study, Bouman & Jacobsen's (2002) results indicated a significant Sell-in-May effect in 13 of the 16 countries. Unlike us, they found a significant effect in Japan but not in Australia, Denmark, and Norway as we did.

When we included a January dummy in regression model (2) to account for the January effect, we found a significant Sell-in-May effect in 14 international countries, whereas Australia now turned insignificant. In comparison, Bouman & Jacobsen (2002) observed a significant Sell-in-May effect in 12 of the same 16 countries, as Switzerland turned insignificant. Our findings can be said to be very much aligned with what Bouman & Jacobsen (2002) discovered in their study, although we observe some slight differences in significance between countries. Our results are also in compliance with more recent scientific studies that have validated the existence of the anomaly using out of sample data, particularly the studies of Andrade. et al (2013) and Jacobsen & Visaltanochi (2009).

It is also worth mentioning that the time period used in our study is longer and includes more recent observations than what Bouman & Jacobsen (2002) employed in their study. By accounting for the fact that Bouman & Jacobsen's (2002) data sample ends in 1998, we could argue that the Sell-in-May effect might be even more noticeable today, as we observed a significant Sell-in-May effect in even more countries. On the other hand, the average number of half-year periods for Boumans & Jacobsen's sample period is 38, whereas for our sample the average half-year period is around 80. Therefore, it is not surprising to observe less noisy point estimates for our sample, in other words, we are more likely to observe more statistically significant outcomes with a bigger sample size.

After conducting the Welch's two-sample test, results indicated that the winter period generated significantly higher mean returns in 14 out of 16 countries in addition to sub-period 3 for both US indices. Japan and Australia were the only exceptions for the international countries. Even though Bouman & Jacobsen (2002) did not test the significance of the mean return between the summer and winter period, their findings show that the mean return for the winter period was higher than the summer period in most cases. Subsequently, results from our two-tailed F-test on equal variances indicated mixed results. Only 6 out of 10 countries experienced a significantly lower standard deviation in the winter period. Regarding the S&P 500 index, all sub-periods encountered a significantly lower standard deviation in the winter period. For the DJIA index, the results were different, with only sub-period 1 generating a significantly lower standard deviation in the winter period. Accounting for the difference in standard deviation, Bouman & Jacobsen (2002) also showed that the standard deviation was slightly lower for the winter period in most cases. Yet, they did not test the significance of these results.

We included the Sharpe ratio as a performance metric in order to better examine the risk-adjusted return on the two investment strategies, which led to some interesting results. We experienced a higher annual Sharpe ratio for the Sell-in-May strategy in 18 out of 22 countries and sub-periods. In Haggard & Witte's study from 2010, they experienced similar results by comparing the two investment strategies. Investing only in the Buy-and-Hold portfolio generated a Sharpe ratio of 0.117, whilst investing in the Sell-in-May portfolio generated a Sharpe ratio of 0.168 (Haggard & Witte, 2010). Their results showed to be statistically significant at the 1% level. Meaning that the Sell-in-May strategy has a significantly higher Sharpe ratio, based on a 1% significance level. Our research differs from Haggard & Witte in the way that we compute and test the different Sharpe ratios for a magnitude of countries/indices. In summary, our results revealed that in 10 out of 16 international countries, the Sell-in-May strategy encountered a significantly higher Sharpe ratio at either the 1%, 5%, or 10% level. For the US indices, every sub-period faced Sharpe ratios that were not significantly different from one another.

The estimation results for the Sell-in-May strategy provided by Bouman & Jacobsen (2002) show that all Jensen's alpha coefficients are different from zero. To check how reliable these results are, a significance test was applied. In 11 out of 18 countries, the estimated alpha coefficient is statistically different from zero at the 10% significance level (Bouman & Jacobsen, 2002). Our estimation shows that the results are significant at the 10% level in 16 out of 22 countries and indices. The only international countries or indices where the results are insignificant are sub-period 1 and 2 for S&P 500 and DJIA, Australia, and Japan. Bouman & Jacobsen (2002) also found the results for Australia to be insignificant, but they did not find the same result for Japan. If we disregard the two first sub-periods for the US indices, the results are significant in 16 out of 18 countries/indices. These findings are remarkably similar to those of Bouman & Jacobsen (2002), although our results are of greater significance. As previously discussed, one possible explanation for the discrepancy in significance might be that we employ longer time periods in our study compared to Bouman & Jacobsen (2002).

All alpha coefficients calculated from the Fama-French 5-factor model were positive. However, the results indicated that 8 out of 16 international countries, as well as sub-period 3 for the US indices, experienced statistically significant alpha coefficients. We can therefore conclude, that in 8 of the international countries in addition to the US market, the abnormal returns cannot be explained by the known risk factors.

Additionally, in their paper, Bouman & Jacobsen (2002) includes a figure for the Italian market that demonstrates the cumulative return regarding both trading strategies. The figure clearly illustrates that the Sell-in-May strategy generates a higher total amount of return compared to the Buy-and-Hold strategy for the Italian market in the period 1973 to 1996 (Bouman & Jacobsen, 2002). The scientists state that the results are akin for the remaining countries examined. We observe similar findings as Bouman & Jacobsen (2002) over the cumulative return for Italy in appendix A2. For the remaining international countries, the tendency is also that cumulative return is higher for the Sell-in-May strategy. The only exception being Switzerland. Still, our results are in line with the results presented by Bouman & Jacobsen (2002).

7. Conclusion

The objective of this chapter is to conclude the most important findings of our thesis. In addition to providing answers to the problems stated in section 1.2 in a short and concise matter.

Findings discovered through the time series regression implicated an existing significant Sell-in-May effect in 15 of 16 international countries examined. This discovery supports previous research on the subject and shows that the Sell-in-May effect is still observable in financial markets today. The results further confirm the persistence of the Sell-in-May effect across markets, which leads us to question Fama's Efficient Market Hypothesis, as the anomaly does not seem to diminish over time.

By applying the regression models on different sub-periods for two US indices, results indicated a statistically significant Sell-in-May effect solely for sub-period 3. Implying that the Sell-in-May effect has only existed in the market over the last 50 years. Comparatively, the market anomaly was non-existent in sub-period 1 and 2, as results were insignificant for both indices. These respective findings are also in compliance with other academic studies on the topic. Further, we tested the possibility of the January effect being the Sell-in-May effect in disguise. We rejected this possibility through statistical testing where we found that the Sell-in-May effect was autonomous from the January effect in all international countries in addition to sub-period 3 for both US indices.

Testing for equal mean returns between the summer and winter period, findings indicated that 14 out of 16 countries, as well as sub-period 3 for the US indices, generated a significantly higher mean return for the winter period. For the equal variance test, our findings showed that in 6 out of 10 countries, all sub-periods for the S&P 500, and sub-period 1 for DJIA, generated a significantly lower standard deviation for the winter period. In terms of mean returns, we can conclude that the months of November to April generated higher returns compared to the rest of the year.

Additionally, we simulated and tested two trading strategies to examine whether investors could exploit the Sell-in-May effect and implement it into their trading strategy. Even though the results were mixed for the US indices, findings indicated that for most international countries, the Sell-in-May strategy outperformed the Buy-and-Hold strategy in terms of Sharpe ratio and alpha. Sharpe ratios for the Sell-in-May strategy were significantly higher than the Buy-and-Hold in 10 out of the 16 international countries. These findings indicate that the investor could exploit and profit from the anomaly. Further, we can conclude that it is highly unlikely that the Sell-in-May effect is driven by a higher level of volatility in the winter period.

Supplementary, we estimated Jensen's alpha through the CAPM in order to test whether the alpha coefficients were statistically different from zero or not. In every country, we experienced positive alpha estimates, pinpointing that the Sell-in-May strategy is outperforming the Buy-and-Hold strategy given its level of risk. Jensen's alpha estimates were statistically significant in 14 out of 16 international countries. By accounting for additional risk factors, alpha estimates from the Fama-French 5-factor model were positive for all countries and indices, and statistically significant in 8 out of 16 international countries, in addition to both US indices. These results demonstrate that the Sell-in-May effect still prevails in financial markets, even after accounting for size, value, profitability, and investment risk factors.

Today, 20 years after the first publication regarding the Sell-in-May effect, academic studies have yet to come up with a valid explanation for the existence of this market anomaly. Potential future research concerning this topic would therefore be to examine other possible causes behind the existence of the effect. Potential causes that we find interesting to further investigate include trading volume, interest rate, and length of vacations.

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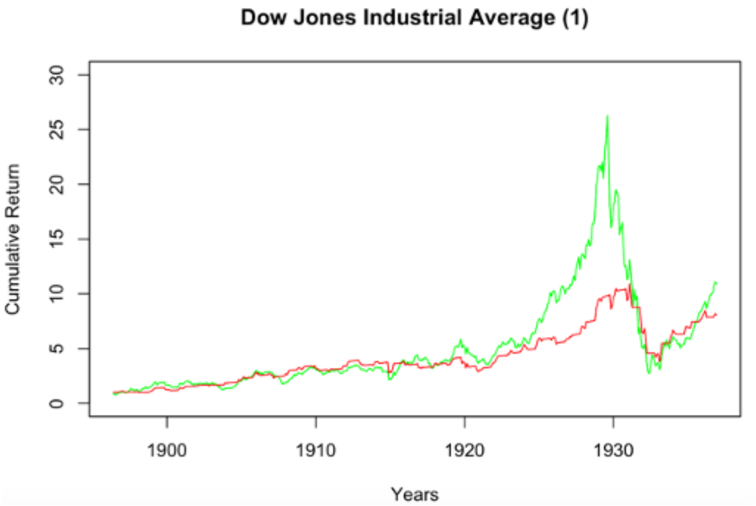
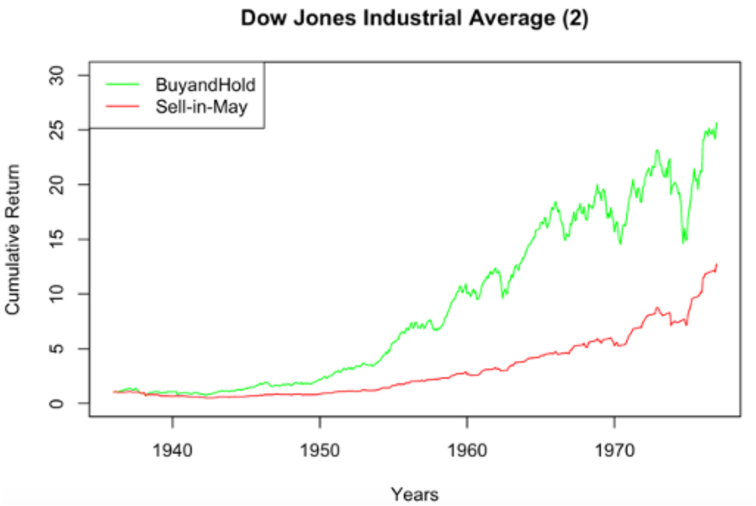
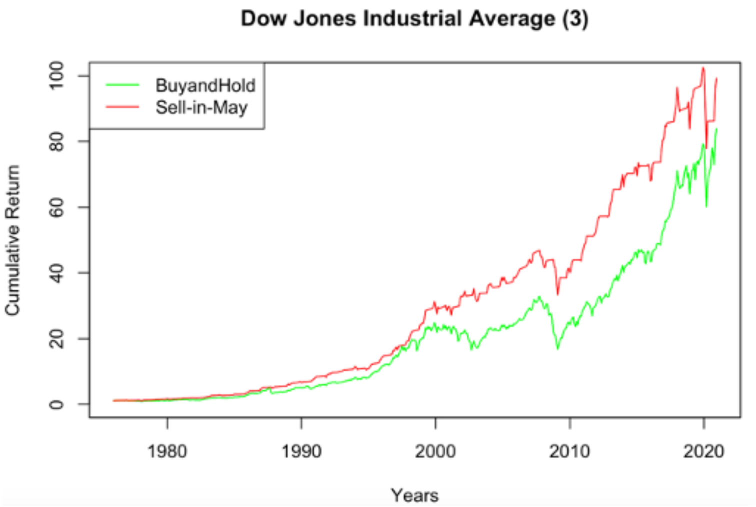
9. Appendix

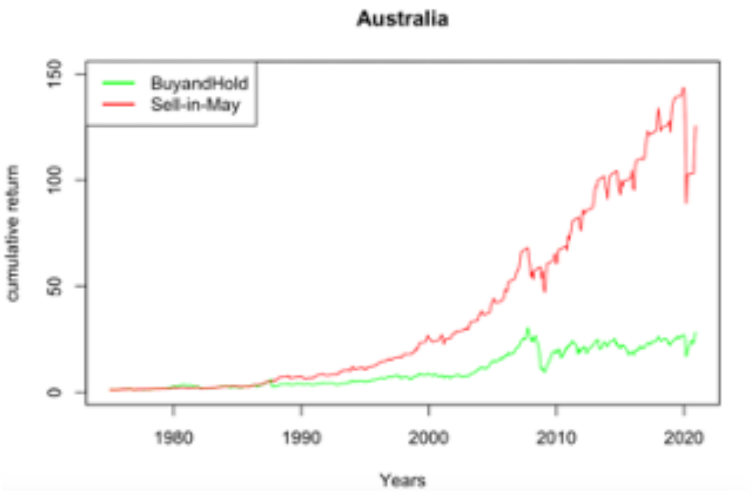
A1 - Cumulative Returns for Dow Jones Industrial Average

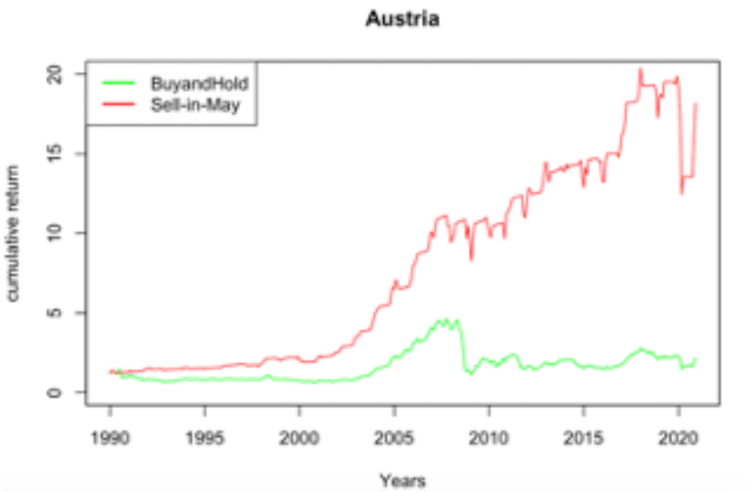


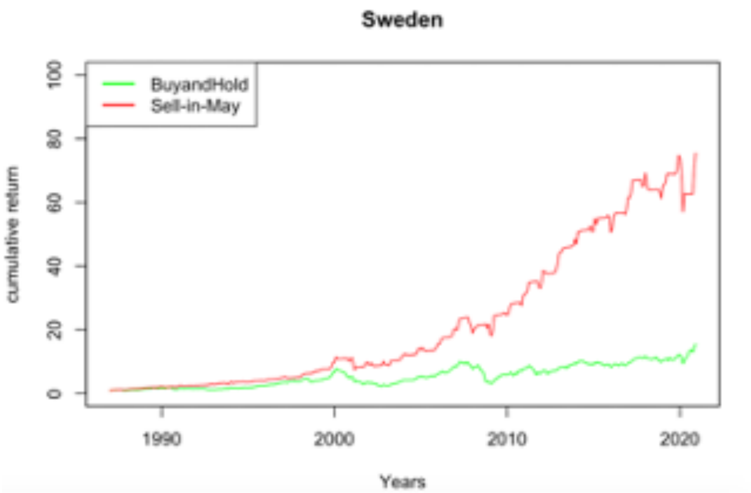


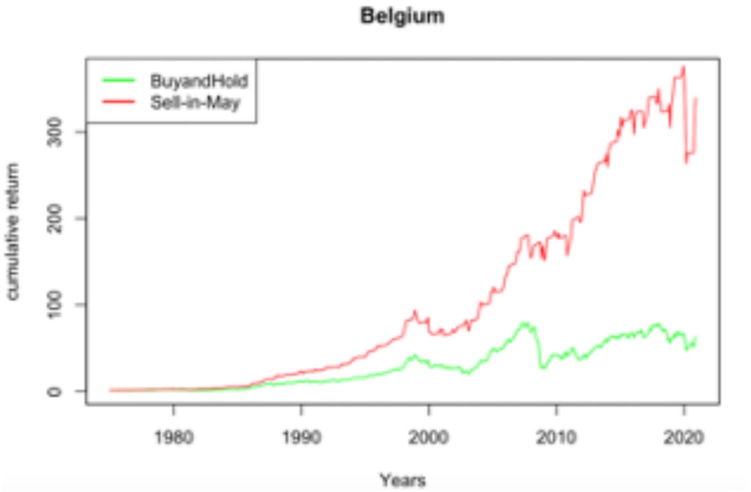


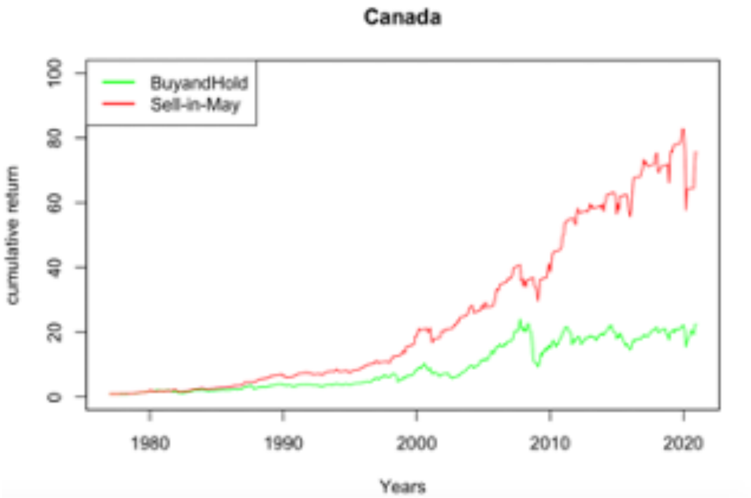
A2 - International Cumulative Returns



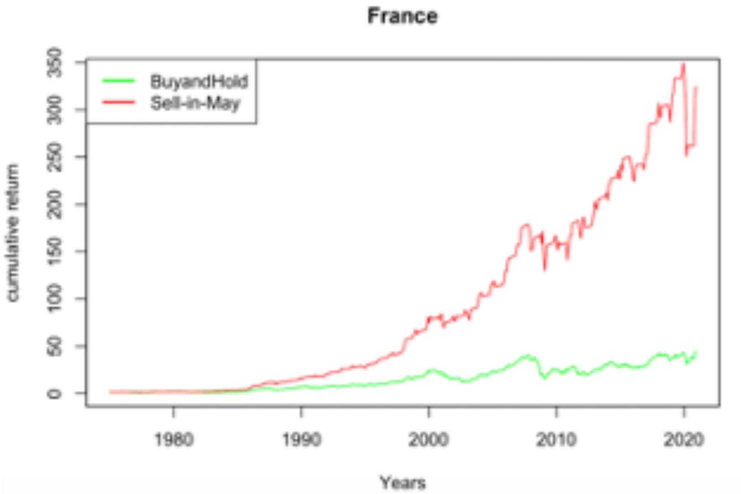




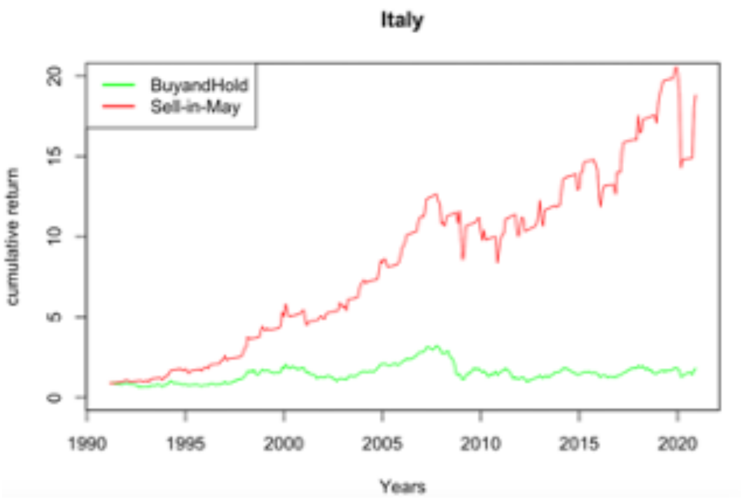

Belgium
BuyandHold
Sell-in-May
cumulative return
0
100
200
300
1980
1990
2000
2010
2020
Years

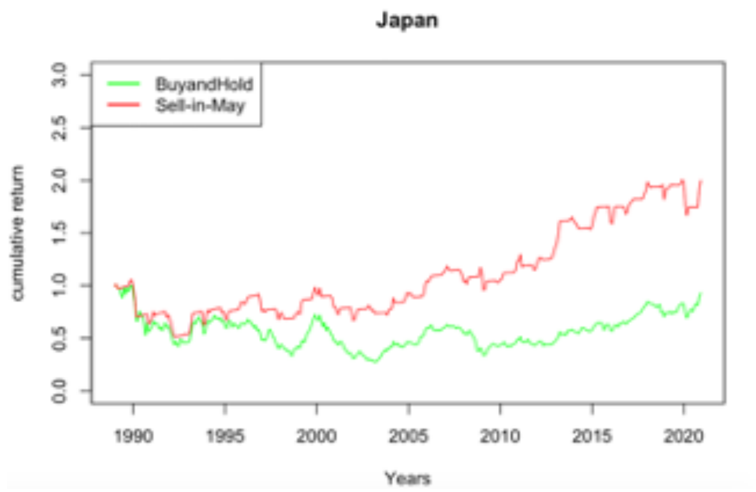

Canada
BuyandHold
Sell-in-May
cumulative return
0
20
40
60
80
100
1980
1990
2000
2010
2020
Years

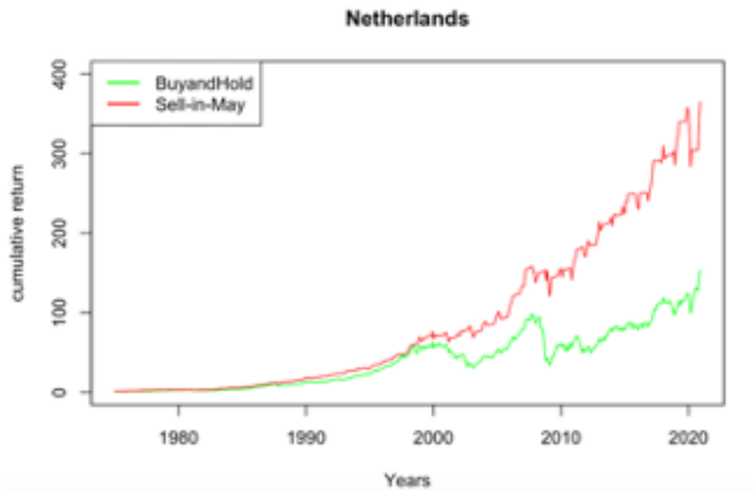

Denmark
BuyandHold
Sell-in-May
cumulative return
0
5
10
15
20
25
30
1990
1995
2000
2005
2010
2015
2020
Years

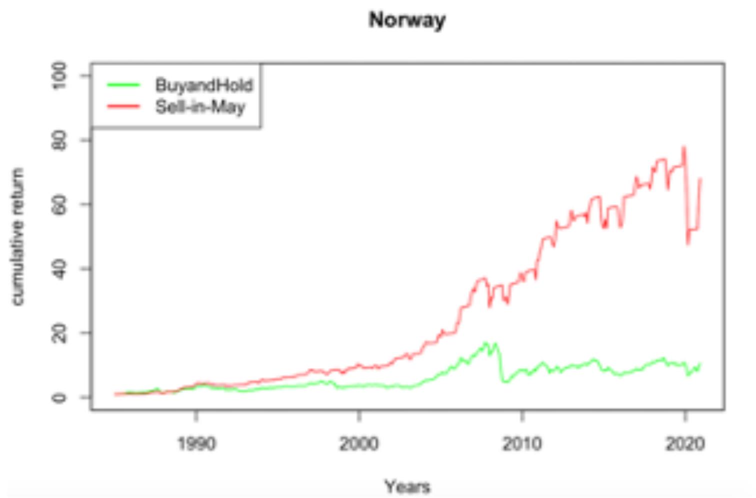

France
BuyandHold
Sell-in-May
cumulative return
0
50
100
150
200
250
300
350
1980
1990
2000
2010
2020
Years

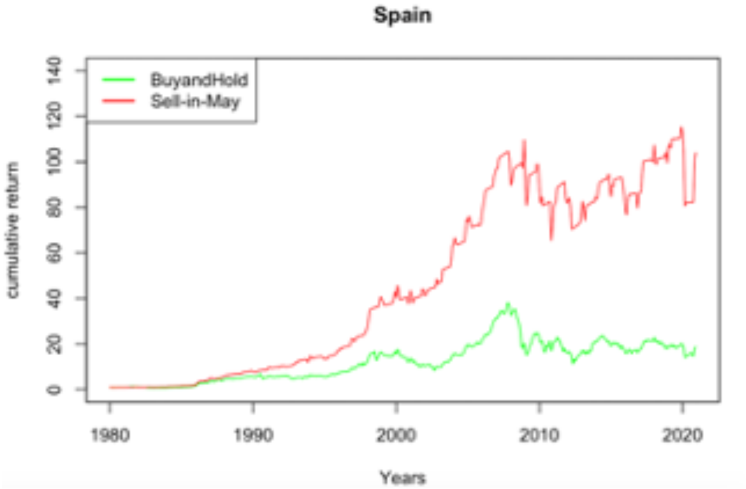

Germany
BuyandHold
Sell-in-May
cumulative return
0
20
40
60
80
100
1980
1990
2000
2010
2020
Years

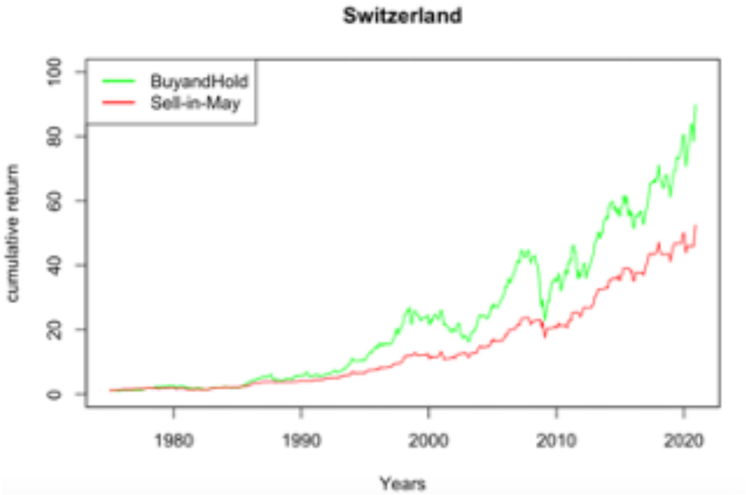

Italy
BuyandHold
Sell-in-May
cumulative return
0
5
10
15
20
1990
1995
2000
2005
2010
2015
2020
Years

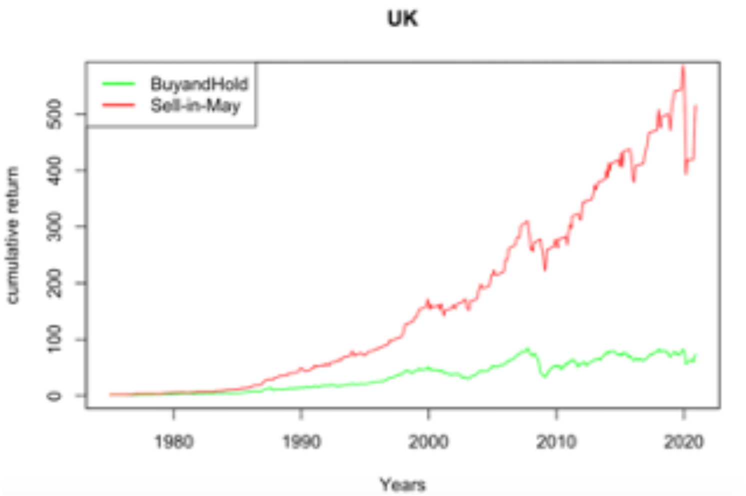

Japan
BuyandHold
Sell-in-May
cumulative return
0.0
0.5
1.0
1.5
2.0
2.5
3.0
1990
1995
2000
2005
2010
2015
2020
Years


Netherlands
BuyandHold
Sell-in-May
cumulative return
0
100
200
300
400
1980
1990
2000
2010
2020
Years


Norway
BuyandHold
Sell-in-May
cumulative return
0
20
40
60
80
100
1990
2000
2010
2020
Years


Spain
BuyandHold
Sell-in-May
cumulative return
0
20
40
60
80
100
120
140
1980
1990
2000
2010
2020
Years


Switzerland
BuyandHold
Sell-in-May
cumulative return
0
20
40
60
80
100
1980
1990
2000
2010
2020
Years


UK
BuyandHold
Sell-in-May
cumulative return
0
100
200
300
400
500
1980
1990
2000
2010
2020
Years

A3 - Discussion Paper Audun Przytula Fjeldberg - Responsible

As a part of the master thesis, we are obligated to write a discussion paper concerning the competency goal “international” or “responsible”. These two competency goals are both a part of the University of Agder School of Business and Law key concepts together with innovative. Throughout the two years of our master’s degree, these concepts have been integrated into our courses. These three concepts will also be relevant later in life when it comes to future jobs. In this discussion paper, I will discuss how our topic, hypotheses, and findings are related to the concept of “responsible”.

Master Thesis

The study conducted for this master thesis focus on seasonality in stock market returns. The main focus regarding the seasonality in stock market returns, will be towards the well-known phenomenon known as the Sell-in-May effect or the Halloween effect. Our thesis will examine whether the months November to April (winter months) generates higher returns compared to the months of May to October (summer months). We also check if the so-called January effect can be one of the reasons for the existence of the Sell-in-May effect. To conduct this study, we used a quantitative approach since all of the data used only consists of numbers. In order to check for the Sell-in-May effect, we apply a regression model to check for statistical significance. An expansion of the regression model is also used to examine if the Sell-in-May effect can be explained by the January effect. Bouman & Jacobsen (2002) used the same regression model as the one we applied. Further on we also test if a higher level of risk in the winter months can be an explanation for the differences in the returns. Lastly, we developed two trading strategies. One trading strategy would invest in the stock market from November to April, and in risk-free rate for the remaining months, to check if it would be possible to exploit the Sell-in-May effect into a trading strategy. The second trading strategy would be a normal Buy-and-hold strategy that would be fully invested in the market for the whole year.

The empirical results from our analysis showed some interesting results regarding the Sell-in-May effect. We observed that the Sell-in-May effect was present and statistically significant in 15 countries and in sub-period 3 for both US indices. By testing for equal means between the winter and summer period, our tests also showed that 14 out of 16 countries generated a statistically higher mean return for the winter period. Comparing the Sell-in-May strategy and the Buy-and-Hold strategy, the Sell-in-May strategy generated a higher Sharpe ratio in 18 out of 22 countries and indices. Only 10 of these observations were statistically significant. Applying both the Capital Asset Pricing Model and the Fama-French 5-factor model, our findings indicated that the Sell-in-May effect still existed in the markets after accounting for other risk factors than only systematic risk.

An important part that is one of the fundamentals of our thesis is the financial markets. We are using a total of 16 countries, in addition to two US indices. The two US indices are the Standard and Poor 500 (S&P 500) and the Dow Jones Industrial Average (DJIA). For the 16 countries, the length of the time period was from around 1970 to 2020, while for the US indices, we had data as far back as 1870. All the data consists of monthly returns. We have no information on what type of firms that were listed on the indices that these monthly returns are calculated from. The definition of "responsible" may also have changed throughout the years. An action that may have been defined as responsible in for example 1910, may not be applicable to what we will define as responsible today. Overall I do not see a clear connection between the topic of our master's thesis and the concept of "responsible". I will try to present some thoughts on what I see as responsible.

Today, many companies are focusing on becoming greener and acting more responsibly towards the environment. Environmental, Social, and Governance (ESG) have become extremely popular in the last years. This is something that we as students at the University of Agder also have experienced. Some of our courses have had a main focus on sustainability. Sustainable Capitalism and Environmental, Social and Governance (ESG) Metrics: Reshaping Finance are two of the courses I have had that have had a focus on sustainability. Combining the knowledge obtained from these courses and combining them with analytical courses like Econometrics, Investments, etc. have given me a deeper understanding. Especially when it comes to responsibility.

When investing in the stock markets, there are some useful sources that may help the investor to find more responsible companies. ESG ratings are becoming more and more popular for investors, and companies strive to improve their social responsibility. Still being one of the biggest energy suppliers in the world (Atashbari et al., 2018), the oil and gas sector have experienced a need to reduce their Green House Gas (GHG) emissions to become greener. A reason for this is because this sector has had a huge impact on the environment throughout history (Gimenes et al., 2017). As an investment object, energy suppliers tend to be popular.

Since more investors are focusing on greener investment objects, these sectors need to change. To help investors pick out greener companies, MSCI has provided a lot of useful help by providing support tools and data for investors. MSCI provides data that shows how well different firms perform when it comes to sustainability and responsibility towards the environment (MSCI, 2022). As a part of getting better ratings, the companies need to report their emissions correctly.

In the later years, there have been a lot of new reporting standards when it comes to sustainability. A well-known reporting standard for sustainability reporting is The Global Reporting Initiative Standards (GRI Standards) (GSSB, 2016). The Global Sustainability Standards Board (GSSB) developed these standards as a tool for the companies. By applying these standards into their reporting, companies can take responsibility for their impacts on the economy, the environment, and society (GSSB, 2016). When a company is going to report about their material topics like GHG emissions, they will need to follow the requirements found in the reporting standard GRI 305: Emissions. These standards are all based on the requirements found in the GHG Protocol Corporate Accounting and Reporting Standard (GSSB, 2016). The GHG protocol contains three different classifications of GHG emission, which are presented as Scope 1, Scope 2, and Scope 3 (GSSB, 2016).

The first classification of the GHG emission is called scope 1, which accounts for the direct GHG emissions. The second classification is known as Scope 2, and accounts for the indirect energy emissions. What separates scope 1 and scope 2 is that the emissions in scope 1 are all linked with the operations that the company owns or controls by itself, while scope 2 is linked with all the consumed energy that the company has purchased from others (WRI, 2004). The last classification, scope 3, is not something that the company has to report. This scope accounts for all other indirect GHG emissions (WRI, 2004). Reporting in accordance with these standards can be viewed as responsible.

As we know, the financial markets consist of many different firms that operate in different sectors. Some of these firms operate in sectors such as oil and gas, mining, etc. which may have a bigger impact on the environment. Since the production and usage of minerals like oil and gas may harm the environment more than other renewable energy sources, investors should take this into account when investing in firms that operate in these sectors. Taking a look at the components of the S&P 500 (Slickcharts, 2022), we observe a lot of different listed firms on the index. We observe many well-known firms like Apple, Tesla, Coca-Cola company, Pfizer etc. Especially Apple, Tesla and Pfizer are three companies that have been a lot in the media in the recent years.

Ever since I can remember, there has always been talk about how Apple threat their employees. Since Apple is a firm that outsources their production to China, a huge question has been about the work conditions. I can not remember exactly what's been said about the work conditions, but I do remember their being talk about to low salaries and child labor. As one of the biggest and most popular technology firms in the world, you would expect Apple being able to make sure that the factory workers to have good work conditions. If a huge firm like Apple do not make sure that the factory workers have a good and safe environment to work in, Apple is not acting responsible. It can be looked at like Apple than takes advantage of the poorer people in China, which is not ethical.

Looking all the way back at the three first years (bachelor's degree) at the University of Agder, I also remember an exam in ethics where we had a case about Tesla. This case stated that the factory workers in the US also had horrible working conditions. There were long days and a lot of physical work. Because of the long days of physical work with few breaks, I remember that the case stated that one of the employees got back problems. This is something that can happen when a person puts a lot of physical pressure on their body, but it could also been avoided. A reason for the back injury was due to part of the car the employee was working on, which lead to a lot of pressure on the back because of a lot of bending of the back.

Pfizer is one of the companies that has been most in the media the recent years. Due to the Covid-19 pandemic, Pfizer has been one of the biggest suppliers of vaccines against the Covid-19 virus. They have provided vaccines to basically the whole world, together with some other medical firms as well. Even though they act responsible trying to fight the pandemic, the producers of vaccines and other medications have been questioned about they operate. In many occasions, especially in the US, we read news about medical firms that prices their medications etc. at very high levels. These firms are supposed to help people who need medications, vaccines, etc. Instead some of the firms take advantage of the people in need, by pricing the medications at an extremely high level. They are acting like they are responsible, but the way the price their products does not seem ethical.

The things I have presented in the text so far are all things that can be related to the concept of "responsible". The firms have a huge task when it comes to acting responsible and ethical towards society. Acting responsible can happen in many different ways. By lowering the GHG emissions and trying to come up with new ways to produce cleaner and greener energy sources, a firm can be said to act responsible, as long as they report their emissions correctly. For other firms like the two examples of Apple and Tesla, they will need to make sure that they provide their employees with good working conditions, that will not affect their health. Medical firms like Pfizer have a huge task when it comes to responsibility. They provide products that may improve or save someone's life. The question here is whether these types of firms should favor profit over pricing their products at an affordable level.

With all that have been mentioned in the text I do not see a clear connection between what I assume to be responsible and the topic of our master's thesis. It is not directly connected. We have used stock markets in our analysis, but we cannot control which firms that are listed on the indices applied. The firms listed on each of the indices may act in totally different ways. Some of them may act more responsible than others, while some of them may not act responsible at all. The financial markets are such huge markets, so it will be difficult for all the listed firms to act in the same way. Regarding the oil and gas sector compared to a firm that produce renewable energy, the oil and gas sector will not be as responsible as the renewable energy sector. Some of the points that have been mentioned is my own thoughts on the subject on how to act responsible. It is again worth mentioning that our thesis can be indirectly linked to the concept of "responsible" due to how the firms that are listed on the indices we have applied acts towards the society and environment.

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A4 - Discussion Paper Emil Sebastian Konsmo - International

Before I start to discuss various international trends and elaborate on how they are related to this master thesis, I find it important to give the reader a somewhat comprehensive introduction to the subject of our master thesis.

The title of our master thesis is “Seasonality in Stock market returns”. There is a widely known market anomaly called the Sell-in-May effect. The Sell-in-May effect refers to the fact that stocks tend to perform far better during the winter months, compared to the summer months, in terms of stock market returns. There is an old saying that goes as far back as 1697 which illustrates this common wisdom: “Sell in May and go away”. May marks the start of a period in which investors expect to get reduced returns. The trading strategy suggests investors would be better off by selling their stocks/positions and switching to cash/holding bonds from May through November (hence the summer period) and then returning to the stock market during the winter period (November – April). The first known academic research that documented the Sell-in-May anomaly was the study of Bouman & Jacobsen (2002). By using data from the period from January 1970 until August 1998, their seminal study provided evidence of a Sell-in-May effect in 36 out of 37 countries. Their results were later confirmed by the studies of Andrade et al. (2013), Degenhardt & Auer, (2018).

This master thesis is greatly inspired by this academic paper by Bouman and Jacobsen (2002). In our paper, we have constructed several research questions that we will try to find an answer to. Firstly, our paper aims to investigate the historical strength of the effect by analyzing 150 years of data containing the monthly market returns for two US stock market indexes, the Standards & poor 500 and the Dow Jones Industrial Average index. Additionally, we are examining whether the Sell-in-May effect is a worldwide phenomenon, and we do so by applying a time series regression model on monthly data from a total of 16 different international countries in addition to the US stock market indices.

There is another widely known calendar anomaly called the January effect, which indicates that the month of January is typically the best performing month in terms of stock returns. And because January is included in the winter months, some researchers argue that the Sell-in-May effect is driven solely on the higher returns of January.
Therefore, our study also examines whether the Sell-in-May effect is just the January effect in disguise. Meaning how much the January effect contributes to the Sell-in-May effect. We do so by adding a January dummy variable to the same regression models.

Additionally, we construct and compare two different investment strategies in order to examine whether it is possible for the investor to exploit and profit from the calendar anomaly. The Sell-in-May strategy holds a market portfolio during the winter months (Nov-April) and then switches to holding risk free rate over the summer months. In our case the risk-free rate constitutes long term government bonds with 10 years to maturity. Buy-and-Hold is the benchmark strategy which is fully invested in the market portfolio through the full year.

To summarize, our thesis is taking a quantitative approach to analyzing market trends in various international stock markets. Our findings based on our regression models indicated that stock market returns in the winter period was significantly higher than the summer period in 15 out of 16 countries examined. Further, the results indicated that the January effect cannot be used as a reasonable explanation for the Sell-in-May effects existence. Lastly, the high returns in the winter months cannot be explained by a higher level of risk in these months.

In the next section of this paper, I am going to draw parallels and deliberate how this thesis relates to international trends and forces. In order to do so, I will start by introducing the reader to which international forces and trends I find connected to my thesis, before I draw any parallels or discuss how they are related to my topic. Additionally, as we are writing our study on various international stock markets, I want to discuss arguably the largest determinant to the performance of financial markets, namely governments and their monetary policies.

One specific trend that must be accounted for in this paper, is that over long-time horizons, all national stock markets are experiencing an upward trend in equity prices. In the paper of Kasa, K (1989) the researcher gives evidence for several common stochastic trends in financial markets for the United States, England, Japan, Canada and Germany. The benefits from foreign diversity have probably been exaggerated in the literature for investors with longer holding periods, according to his calculations of factor loadings. Since international markets are perfectly correlated over long time periods when there is a single common stochastic trend (Kasa, 1989).

Our thesis is analyzing stock market data from a total of 17 countries, including the two largest stock market indexes in the United States, namely the Standards and Poor 500 and the Dow Jones industrial average. For the remaining 16 countries, we have utilized data from the value-weighted MSCI reinvestment index. As mentioned earlier, our theses compare two different investment strategies, the sell-in-May strategy and a Buy-and-Hold strategy (benchmark market portfolio). In order to get a better visualization of how the strategies would perform, we computed and plotted the cumulative return for each country. The cumulative return shows us how much 1 dollar invested in the market at the beginning would be worth at the end of the investment period. What I want to achieve with this point, is that for all countries, the plots of cumulative return look indistinguishable. The graphs for all countries have a clear upward trend, which is indeed very much aligned with what Kasa (1989) states in his paper.

Further, I want to elaborate on how financial markets over the world have arrived at this level of connectivity.

In the article of Dobbs, Manyika & Woetzel (2015) the authors elaborate on four global forces that are breaking all trends. The fourth and last force is the degree to which the world is far more connected thanks to changes in trade and capital, people, and information flows.
The story of globalization has traditionally included trade and finance, but there has been a fundamental shift in recent decades. The global trade system has evolved into a complicated, intricate, vast network, rather than a set of lines connecting major trading hubs in Europe and North America. Asia is now emerging into the greatest trading region in the world. Over the last decade, "South-South" trade flows between emerging nations have doubled their proportion of world commerce. China's commerce with Africa increased from $9 billion in 2000 to $211 billion in 2012. Between 1980 and 2007, global capital flows increased by 25 times. In 2009, over one billion people crossed international borders, which is more than five times the number in 1980. These three forms of linkages all came to a halt during the global financial crisis in 2008 and have only gradually returned ever since (Dobbs et al., 2015). As trade and flow of capital goods between nations increases, countries' economies become more connected and dependent on each other. This again would lead to financial markets trending in the same direction since as they all rely on each other. This example can be illustrated in our master thesis, as we can see that the prominence of the Sell-in-May effect moves in similar directions between a large number of international markets.

Perhaps the largest driver and force of financial markets, specifically governments, and their monetary policies cannot be omitted in this paper. In my 5 years of studying economy at the school of business and law at UIA, it has become very clear to me that governments wield a great deal of power over the free market. The fiscal and monetary policies that governments and their central banks have put into action have a significant effect on the financial marketplace. For example, the US Federal Reserve can effectively slow or speed up economic growth within the country by increasing or decreasing interest rates. According to Philip Hildebrand (2006) who is a board member at the Swiss National Bank, "It is through the financial markets that monetary policy affects the real economy". In other words, financial markets serve as the link between monetary policy and the real economy in the transmission mechanism.

In order to keep financial markets as stable as possible, central banks often implement goals to keep the inflation rate constant at around 2%. If this central bank's credibility is such that market participants anticipate that inflation will remain firmly fixed at 2% in the long run, then the 10-year inflation-indexed bond will always reflect a 2% inflation rate in ten years. Should it happen, however, that central banks get too comfortable with the fact that market assumptions reflect stable inflation expectations, it may diverge from the correct policy path over time. Markets will eventually detect the policy flaw. In such an admittedly extreme scenario, the market's likely reaction would be a sharp revision in inflation expectations, with the central bank's credibility costing it dearly (Hildebrand, 2006).

In today's global financial market, one can argue that this exact scenario has become true. At the time of writing, inflation numbers are hovering at an astonishing 8,3 percent in the United States (the highest recorded inflation in 40 years). The president of the United States, Joe Biden, has just announced on the news that his top priority is to "fight" inflation. Approximately at the same time, the Chairman of Fed, Jerome Powell, in his latest speech vowed tough action on inflation, stating that it is jeopardizing an otherwise strong economic recovery. What the global economy is experiencing now, is the aftermath and consequences of what it costs for central banks to create the V-shaped recovery after the Covid-19 crash. From the plots of cumulative return in our master thesis, we clearly observe that in the beginning of 2020 the S&P 500 fell by 34% and bounced back to previous all-time highs just 4 months later. The fast market recovery can arguably be explained by the US federal reserve's acceleration in quantitative easing, more commonly known as money printing. In December 2019, according to data found on Fred economic data the total M2 money supply of US dollars was at 15 300 billion USD (15,3 trillion). As of February 2022 however, the M2 money supply has increased to a staggering 21 750 billion USD (21,75 trillion). With this sharp of an increase in new dollars circulating in the economy, a loss in yearly purchasing power of 8,3% seems low compared to the 42% increase in US dollar supply in the period from December 2019 to February 2022. So far this year, the US technology index Nasdaq is down over 4000 points (26%). Whilst the S&P 500 is down 16%, which is the worst year to date performance since World War II.

To summarize, the prices of financial assets between countries are highly connected and dependent on each other. Additionally, over longer time horizons, national stock markets are trending in an upwards direction. Financial markets have reached to this level of connectivity, thanks to globalization, by big shifts in trade and capital, people, and information flows. Further, we have elaborated on how much governmental and monetary policies influence the performance of financial markets and the global economy in general. Lastly, it must be stated that I found it extremely challenging to find direct links between the broad concept of "international" and the specific topic of our master thesis.

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