UNIVERSITY OF GOTHENBURG
SCHOOL OF BUSINESS, ECONOMICS AND LAW

Bachelor's project within the Business and Economics Bachelor Programme

Sell in May and Go Away:
A Historically Viable Investment Strategy?

Abstract:

This thesis investigates if the efficient market hypothesis holds, despite the pattern of the sell in May effect. Since we cannot study the entire stock market, we have chosen the S&P 500 as a proxy because it is an old and well-tracked index that should be efficiently priced. An OLS regression that compares seasonal returns is used to determine the existence of the effect and the regression shows that there is a statistically significant sell in May effect present in the S&P 500. Another regression is done comparing monthly returns, showing that January has significant positive returns while September has significant negative returns. January is ruled out as the possible cause of the sell in May effect but when controlling for September the difference in seasonal returns becomes insignificant. This indicates that September could be the cause behind the sell in May effect in the S&P 500. Thereafter, we construct two portfolios: one that divests from the market and invests in a T-bill during the summer season, and another that does the same in September. These two lower-risk portfolios, timing the market based on a historical pattern, yield higher returns than the index, therefore contradicting the efficient market hypothesis.

Bachelor thesis 15 hp

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1. Introduction

1.1. Background

"Sell in May and go away" is an old adage that advises investors to sell their positions in May and return to the market in the fall. While the exact origins of the saying cannot be pinpointed, it is believed to come from London's financial district as the saying originally had the addition of "come back on St. Leger's Day". Referring to a horse race in Yorkshire, the phrase was an endorsement to wealthy British investors to sell their shares during their summer holiday and reinvest in the market after St. Leger's Day which takes place in the autumn.[1] The advice was based on the historical perception that the stock market has lower returns in the summer months.

Whether this perceived pattern corresponded to reality was first studied by Sven Bouman and Ben Jacobsen in 2002. Their study conclude that stock market returns indeed are higher in the November-April period than in May-October. Being the first scholarly response to this specific market anomaly, the study finds presence of the Sell in May effect in 36 out of 37 countries used in their sample.[2] 16 years later, in 2021, Jacobsen together with a new co-author, Cherry Y. Zhang, revisits the study. They find that the effect had not only persisted but had become more statistically significant as well.[3]

Their findings corroborate the popular stock market adage but contradicts Eugene Fama's Efficient Market Hypothesis (EMH). The EMH states that all available information at the time is incorporated and reflected in an asset's price, therefore making it impossible to time the market. A consistent divergence in stock returns during the summer for no apparent reason violates the efficient market hypothesis and presents a market anomaly. In an efficient market investor would use the information that is given, adjust their investment strategies, and the market anomaly would be arbitraged away.

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[1] Bouman, S., & Jacobsen, B. (2002). The Halloween Indicator, "Sell in May and Go Away": Another Puzzle. *The American Economic Review*, 92(5).
[2] Ibid.
[3] Zhang, C. Y., & Jacobsen, B. (2021). The halloween indicator, "Sell in May and Go Away": Everywhere and all the time. *Journal of International Money and Finance*, 110.

There are various well-known calendar anomalies such as the January effect, the days-of-week effect and the turn-of-the-month effect. The January effect, the phenomena that stock markets during January generally tend to outperform the rest of the year, is said to be explainable by tax-loss harvesting.[4] Investors sell off stocks that are losing in December and repurchase them in January with the intention of reducing their capital gains, therefore it is not an anomaly that would be profitable to exploit. The days-of-week and turn-of-the-month effects refer to the phenomena that the prices of securities tend to increase at the end of the week and at the end of the month, respectively. These anomalies are less explainable, however exploiting them would lead to substantial transaction costs as it would require multiple trades a year, hence the profitability is low to none.[5]

The "Sell in May and go away" anomaly is not easily explainable as there is no evident reason or group of factors behind it. Unlike the January effect, there is no established reason for why it occurs, and in contrast to the turn-of-the-month effect and the days-of-week effect, an investment strategy to take advantage of it would only require two trades a year. The "Sell in May" anomaly could therefore be appropriate to exploit when attempting to beat the market.

1.2. Problem Description

According to the adage, the original strategy would advocate to sell your positions in May and hold cash during the summer months. The reasoning behind "Sell in May and go away" is that the stock market on average underperforms during the summer months when compared to the rest of the year, however this does not necessarily mean that the period yields a negative return. If the summer months tend to result in a smaller but positive capital gain than the rest of the year, selling and holding cash would in turn be a losing strategy. If the 6-month period May-October does indeed yield a positive, yet significantly smaller return than the rest of the year, a winning strategy may be an alternative investment in the summer months. A rotation in the portfolio could exist, separate from market-index returns, that proves to be a better investment alternative than holding the index year-round.

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[4] Haug M., & Hirschey, M. (2006). The January Effect. *Financial Analysts Journal*, 62(5).

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

1.3. Purpose

The first aim of this thesis is to examine whether the “Sell in May and Go Away” effect is observed in the S&P 500. By looking at historical data we want to establish to what extent this pattern has occurred in the market-index and determine its statistical significance.

The second aim of this study is to investigate if there is a profitable strategy that takes advantage of the given information. Through divesting and rotating an alternative investment during the May-October period, this study’s objective is to determine if a strategy exists that outperforms the annual returns of the Standard & Poor (S&P) 500 index. If it is possible to find an investment that outperforms the S&P 500 during the summer period and has done so consistently enough over a 30-year investment period, then the efficient market hypothesis does not hold.

The main purpose of the study is not to figure out what is causing the anomaly, but rather to determine if it is possible to exploit it based on historical returns of the S&P 500. Since the results are based on historical closing prices and rates, the case may be that the strategy of portfolio rotation would have yielded a better return in the past but will prove too risky to use in the future. As every investor knows, one should generally not base expected future returns on historical returns. The results from this thesis however may cast some doubt on the market efficiency, and at the very least provide an indication for whether Sell in May could be a viable investment strategy.

1.4. Layout of the Thesis

This thesis is structured to provide a comprehensive investigation of the Sell in May effect in the S&P 500 and determine if it can be utilized to beat the market. The organization of the sections is designed to guide the reader through the theoretical foundations, methodological approaches, empirical findings, and conclusions derived from this study. Below is an outline of each section:

The first section introduces the research topic, outlines the research questions, and presents the objectives of the study, also including a brief overview of the thesis structure. In section

two the hypothesis is formulated and presented. Section three summarizes relevant theories used to investigate the Sell in May effect and section four provides a brief review of the existing literature on the Sell in May effect. In section five, the collected data is presented, discussed and revised. Section six details the method used to determine the effect, calculate risk premiums, and evaluate the portfolios. Our findings are presented in section seven and interpreted in section 8 where we discuss the implications of the results and the significance. The main findings from the research and conclusions from the discussion are summarized in the last section which also answers the research question posed. The bibliography and supplementary material are found in the “References” and “Appendix” sections, respectively.

2. Research Question

The first part of this thesis will determine whether the Sell in May effect occurs in the S&P 500 and if it is caused by any individual months. These two questions are fundamental for the second part of the thesis which tests the market efficiency of the S&P 500.

The other previously mentioned seasonal anomalies tend to have shorter time spans as well as logical explanations for why they persist such as taxes or high transaction costs, making them unprofitable to exploit. Their persistence therefore fits the efficient market hypothesis. The Sell in May effect however occurs over several months and would not incur high transaction costs to exploit. If the efficient market hypothesis holds, the following must be true: *There is simply no superior investment alternative to the market during the May-October period.*

Finding an investment strategy that successfully outperforms the market by timing the market based on the Sell in May effect would therefore directly contradict the EMH in the specific market. If a portfolio using said strategy would yield a higher expected return in relation to risk compared to a portfolio that didn't, the results suggest that the market is inefficient.

We will thereby test the efficient market hypothesis by investigating if we can construct a portfolio that (1) outperforms the S&P 500 during the summer period (2) to a lower or equal risk and (3) has done so consistently enough over a 30-year investment horizon? If so, then this could indicate that S&P500 isn't as efficient as previously thought.

3. Theoretical Framework

3.1. Market Anomalies

The literary meaning of the term "anomaly" is an abnormality or a deviation from the common rule. A market anomaly, in a financial context, is when a result is inconsistent with predictions or assumptions based upon models or theories regarding the pricing of assets. When asset-prices deviate substantially from predictions, market anomalies are evidence that core assumptions in theories do not always hold in practice. When a movement, or a certain event cannot be explained by the EMH, a market anomaly consequently becomes an indicator of informational inefficiency.[6]

Market anomalies can be sectioned into three different categories: fundamental, technical and seasonal. The fundamental anomalies refer to abnormalities in the fundamental elements of trading, such as price deviating from predictions after analyzing economic indicators. The technical anomalies refer to the price departing from predictions after conducting a technical analysis, trend projections as an example. Seasonal, or calendar anomalies however are time dependent, meaning that prices deviate from predictions through observed pattern-movements.[7] The Sell in May effect falls into this category, along with others such as the January-effect and turn-of-the-month effect. Seasonal anomalies contradict the weak efficient form since an investor, with knowledge of these patterns, can accumulate abnormal returns.

3.2. Efficient Market Hypothesis

The Efficient Market Hypothesis (EMH) is a financial theory popularized by the American economist Eugene Fama. The hypothesis states that the price of an asset reflects and incorporates all the available information. An implication the theory makes is that it is impossible to outperform the market through timing or stock selection as there are no undervalued or inflated assets. All share prices are therefore theoretically fairly priced and

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[6] Latif, Madiha & Arshad, Shanza & Fatima, Mariam & Farooq, Samia. (2011). Market Efficiency, Market Anomalies, Causes, Evidences, and Some Behavioral Aspects of Market Anomalies. *Research Journal of Finance and Accounting*.
[7] Ibid.

market anomalies are nonexistent due to arbitrage. Hence, in an efficient market, the only factor that affects the asset price is new unforeseen information. Another assumption under EMH is that to be able to yield higher returns, the investment must be riskier.[8]

There are three levels of efficiency to markets, the lowest being weak efficiency. In such a market only all the past prices of an asset are reflected in the current price, thus rendering technical analysis ineffective. The next level is semi-strong efficiency, where all past asset prices and all publicly available information is incorporated in the current price. In a semi-strong efficient market, fundamental and technical analysis are therefore pointless. In the strongest form, efficient markets, even inside information is reflected in the current asset price making insider trading to be a pointless venture.[9]

3.3. Market Risk Premium

The concept of risk premium played a key role in the forming of modern financial theory. As a vital element in both the Capital Asset Pricing Model, and the Modern Portfolio Theory, the risk premium represents the compensations investors are granted for taking on a risk. Based on the rational idea that risk-taking must be more rewarding than a risk-free asset, the risk premium is derived through calculating the difference of a certain asset's return and the risk-free rate of return.[10]

$$Market\ risk\ premium\ =\ R_m - R_f$$

The risk-free asset is a theoretical asset that does not burden the investor with any level of risk. However, since this asset does not exist in reality, treasury obligations of which are reliant on the interest rate are used as a proxy for the risk-free rate. This is because incredibly low default rates have essentially made them a riskless investment. The excess return that the specific asset or market yields is therefore the so-called risk premium, what investors expect to be rewarded with for adding risk to their portfolio. Since investing in the stock market is a somewhat risky venture, the risk premium thus needs to be high enough so that the risk-

[8] Fama, E. F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work. *The Journal of Finance*, *25*(2).
[9] Ibid.
[10] Goetzmann, W. N., & Ibbotson, R. G. (2006). *The equity risk premium: Essays and explorations*. Oxford University Press.

averse participants will be induced to invest. A relatively volatile asset with the attribute of a low or negative risk premium is hence considered a poor investment since the would-be "compensation" for bearing the risk is not nearly enough.[11]

[11] Goetzmann, W. N., & Ibbotson, R. G. (2006). *The equity risk premium: Essays and explorations*. Oxford University Press

4. Literature review

4.1. Bouman, Jacobsen (2002)

The main article on the "Sell in May" phenomena is a journal article published in the American Economic Review in 2002 with the title: *The Halloween Indicator, "Sell in May and Go Away": Another Puzzle*. In it, the researchers Sven Bouman and Ben Jacobsen investigate the anomaly known as the "Sell in May and go away" effect, or "the Halloween indicator". It is explained in the article that to their knowledge the effect has not been thoroughly investigated prior and although the phenomon is frequently cited in media it has only been briefly mentioned in academic literature.[12]

They find that stock market returns are higher in the November-April period than in May-October and that the effect is present in 36 out of 37 countries. The difference in return is considerable, in fact, returns are often negative during the summer months. The effect is particularly strong in European countries but also significant in the US.[13]

They also investigate possible explanations for the effect such as risk difference, cross-correlation between markets and the "January effect" and conclude that the effect cannot be explained by any of these. In the US however, the effect disappears when the January effect is controlled for. The authors also rule out data snooping as a possible explanation and refer to an article from Sullivan, Timmermann and White (1998).[14]

4.2. Jacobsen, Zhang (2021)

In 2021 Jacobsen and another researcher, Cherry Y. Zhang, released another article *The Halloween indicator, "Sell in May and Go Away": Everywhere and all the time.* In the article they re-examine the effect and responded to criticism of the 2002 study. In this updated study they use all available historical data (62 962 observations) on all stock market indices

[12] Bouman, S.,Jacobsen, B. (2002). The Halloween Indicator, "Sell in May and Go Away": Another Puzzle. *The American Economic Review*, 92(5).
[13] Ibid.
[14] Ibid.

worldwide and find that the effect not only persisted in the data but seems to have *increased* in the last fifty years. On average, worldwide returns are 4.2% higher in November-April (winter) compared to May-October (summer). Out of the 114 countries studied, 89 of them have higher returns in winter. 42 of these 89 countries show statistical significance compared to only 1 out of 25 countries that don't.

When looking at 23 developed markets, Jacobsen and Zhang (2021) find that average returns are higher during November-April for 22 of the markets, with Finland being the exception. Out of these 22 markets, the difference is statistically significant in 16 of them. None of the countries located in the middle east and Oceania exhibits significance. By comparing the effect between emerging, frontier and rarely studied markets they also find that the effect seems more pronounced in developed and emerging markets. The study also shows that the size of the effect varied across countries, for instance the US returns are +1.7% higher in November-April and statistically significant at the 10% level.

Additionally, they calculate a new upper bound for equity premium of 4% using this large data set which is significantly lower than the standard 6% used in finance. They note that this equity premium is an upper bound due to survivorship bias and that the premium may have been higher in the recent past due to the unusual growth of several world economies in the last decades. Another finding they make is that worldwide returns during the summer is negative (around -1%) when risk was considered.[15]

4.3. Degenhardt, Auer (2018)

In their article titled "The 'Sell in May' Effect: A Review and New Empirical Evidence," Thomas Degenhardt and Benjamin R. Auer (2018) contribute to the existing research on the topic. Their study involves a comprehensive review of academic literature, comparing various studies, and delving into whether the "Sell in May" effect persisted in highly liquid individual stocks and commodity futures.

[15] Zhang, C. Y., & Jacobsen, B. (2021). The halloween indicator, "sell in may and go away": Everywhere and all the time. Journal of International Money and Finance, 110.

In the conclusion of their paper, they summarize their findings from the literature as follows. The Sell in May effect happens in markets across the world and appears to be stronger in developed markets compared to emerging ones. More recent studies also show that the effect cannot be explained by the January effect (or other calendar effects) nor outliers which disproves previous studies. Regarding the US, the effect also appears stronger and weaker depending on the sector and across stocks with different levels of risk. Contrary to Zhang and Jacobsen (2015), Degenhardt and Auer (2018) gather that the Sell in May effect has *weakened* since the Bouman and Jacobsen (2002) study was published. This indicates that the market is effective. They also conclude that we have yet to find a full explanation to the effect. Finally, their review casts doubt on whether it is possible to exploit the anomaly since it became public information in 2002 and that results from various strategies have been mixed and their performance have generally deteriorated since the study came out.

In their own empirical study, Degenhardt and Auer (2018) look at the effect in the Dow Jones Industrial Average (DJIA) and the future-based commodity sub-indices of the Goldman Sachs Commodity Index (GSCI). This allows them to trace seasonality on the index level to seasonality in specific individual assets. Their findings reveal that the DJIA as a whole experiences a statistically and economically significant Sell in May effect and that the effect is present within many of the individual stocks in the index as well. Basic materials and the industrial sectors experience the strongest Sell in May effect. They note that the strength of the effect has decreased since the 2002 study by Jacobsen and Bouman; however, it is still economically significant in size.

Interestingly the effect is neither economically, nor statistically significant in the GSCI as a whole. Although, many sub-indices within the index prove to have robust Sell in May effects. Just like within the DIJA, the effect is most pronounced in the industrial sector but unlike the stock market the effect appears to have grown stronger in the commodity futures market since the Bouman and Jacobsen (2002) study was published. Degenhardt and Auer (2018), through the citing of a study conducted in 2012, reason that this could be due to solid seasonal supply and demand structures in the physical commodity market. They also propose that the effect may not have gained as much traction among the commodity investors yet since it was first observed in the stock market.

Their findings reveal the presence of the effect, with a stronger manifestation in the stock market compared to the commodity futures market. This outcome aligns with prior research indicating the robustness of the effect, particularly in the industrial sector.[16]

[16] Degenhardt, T., Auer B. R. (2018). The "Sell in May" effect: A review and new empirical evidence. *North American Journal of Economics and Finance*, 43(2018).

5. Data

5.1. Data Description

The data in this study is obtained from the S&P - Capital IQ by S&P Global Market Intelligence. We gather the monthly closing prices of the Standard & Poor's 500 (S&P 500) index beginning from January 31st 1928, up to March 31st 2024. Since the standard prices are obtained, the returns calculated are simple price returns, therefore the data is not adjusted for the income of holding the asset such as dividends. Next, the historical discount rates of the American 3-month treasury bill are obtained from the same database as to be consistent with data-quality. However, due to limitations of S&P - Capital IQ, the data regarding risk-free rates does not date back as far as 1928, the furthest back being the discount rate for the 3-month t-bill, tracked since 1954. Normally, one would use data for the risk-free yield, however since the discount rate has been tracked for a longer period, we calculate the yield from the discount rate, therefore giving a larger number of observations.

We decided to use the S&P 500 when making our analysis for several reasons. Firstly, because it is a broad and diverse index consisting of 500 companies in various industries, therefore it is widely used as a benchmark for the U.S stock market.[17] Secondly, because it is an old and well tracked index, it means that we have plenty of historical data available. Thirdly it is an American index, its companies are on the world's largest stock exchange, thus the 500 companies with the highest market capitalization are among the world's most valuable. Since the index has this attribute, it is interconnected with other stock markets and tends to affect other indices through spillover.[18] Fourthly it's a well-known and closely observed index with plenty of market actors, consequently it should be efficiently priced unlike a lesser-known index with fewer market actors.

[17] Siegel, J. J., & Jeremy D. Schwartz. (2006). Long-Term Returns on the Original S&P 500 Companies. *Financial Analysts Journal*, *62*(1).
[18] von Furstenberg, G. M., Jeon, B. N., Mankiw, N. G., & Shiller, R. J. (1989). International Stock Price Movements: Links and Messages. *Brookings Papers on Economic Activity*, *1989*(1).

5.2. Outliers

When studying a seasonal anomaly such as the Sell in May effect, the ideal method for determining the significance and magnitude of it is to control for all possible variables as they affect the result depending on the time of year they occur. However, this is not possible since there are countless factors influencing the world's financial markets and the task of identifying all of them is a fickle one. One example is controlling for all known market events such as crashes, extreme upswings etc. The issue dealing with this is both the difficult and time-consuming nature of researching all market events. Since it is highly uncertain what time periods were affected by an external influence on the market, definitions would become opaque or incorrect.

This study assumes extreme market events to be uncorrelated with seasonality and therefore in the sense of our research, a "random" variable. With the assumption of extreme market events having the attribute of being random, we determine that such events impact both of the time periods in question equally. However, since the unusual return-values of a market crash or market boom may affect the magnitude of the possible divergence in seasonal returns, outliers are handled in a certain way to reach a more accurate result.

To define an outlier, we use an appropriate method named "fences". This method is used by John W. Tukey in his work *Exploratory Data Analysis* (1977). Through an establishment of the 1st and 3rd quartiles in the data, a multiple of the spread is used to flag the values below and above them.[19] We define outliers as:

$r > r_H + ks_{H-L}$ and $r < r_H - ks_{H-L}$

Where:

$s_{H-L} = r_H - r_S$

Here, r^H and r^L are the 75th and the 25th percentile of the data, respectively. In this case r is the value of the return, as defined under *Method*. The k is a constant, and when used by Tukey, had the value of 1,5 for "inner fences" and 3,0 for "outer fences". According to Hoaglin (2003), the k-value of 1,5 sees the most use in practice, and since the goal of flagging outliers in this study is to reduce the impact of extreme values on averages, the value of 1,5 is suitable for our k.[20]

[19] Hoaglin, D. C. (2003). John W. Tukey and Data Analysis. *Statistical Science*, *18*(3).
[20] Ibid.

With outliers detected, the next action towards the aim of this process is not to remove the observations, nor add dummy variables for the coming regressions, as this would eliminate the fact that the observation had a high or low return. Instead, assigning the values that surpass the fences with the value of the fences, or in other words "cutting" them. This method of handling outliers was used by Galai, Kedar-Levy and Schreiber (2008) when studying outliers in seasonal anomalies, however their detection process differed.[21] Therefore, during the investigation part of this study, where the aim is to evaluate the possible existence of the Sell in May effect, the usage of "revised" returns *R* is present. The revised returns are defined as:

$$R = \begin{cases} r & \text{if} \quad r_L - ks_{H-L} < r < r_H + ks_{H-L} \\ r_H + ks_{H-L} & \text{if} \quad r > r_H + ks_{H-L} \\ r_L - ks_{H-L} & \text{if} \quad r < r_L - ks_{H-L} \end{cases}$$

Details regarding the revised returns are given in Table 8 and Table 9 in the appendix.

[21] Galai, D., Kedar-Levy, H., & Schreiber, B. Z. (2008). Seasonality in outliers of daily stock returns: A tail that wags the dog? *International Review of Financial Analysis*, *17*(5).

6. Methodology

6.1. Sell in May Effect

6.1.1. Monthly Effects

The first step is to investigate and determine the presence, the magnitude and the significance of the Sell in May effect in the S&P 500. Working with the collected monthly closing prices we begin by calculating the price return for each month since January 31st, 1928. We decide to work with price returns instead of total returns for the sake of simplicity and the scope of the study. By determining simple returns, it establishes the index's performance during each single-month long period. The value represents the return of holding for that one specific month, in other words, buying at the very end of the previous month and selling at the very end of the month in question. The monthly return is calculated through:

$$r_t = \frac{p_t}{p_{t-1}} - 1$$

where r_t is the return for month t, p_t is the closing price for month t, and p_{t-1} is the closing price for the previous month.

Further, dummy variables are constructed for each of the 11 months after January, of which serves as the benchmark group. By adding dummies to our regression, we get an overview for the predicted average return of each month. The following regression was run:

$$R_t = \beta_1 + \beta_2 Feb \ \ldots \beta_{12} Dec \ + \varepsilon_t \quad (1)$$

Here, R_t denotes the return for month t, ε_t is the error term for month t and the dummy variables are defined as:

$\{Feb, Mar \ldots Nov, Dec\} = 1$ if the return is observed to take place in that month of the year, and equal to zero if otherwise. Since January is the benchmark group, it is not included as a dummy variable in this regression.

If the effect of an individual month in regression (1) turns out to be significantly negative or positive, that month may be solely responsible for the difference in return between our two periods. To test for the hypothesis that month t may be causing the divergence in returns by either dragging the "summer" average down, or by enhancing the "winter" months performance, the following regression is:

$R_t = \alpha_0 + \alpha_1 Summer\ month + \alpha_2 Significant\ month + \varepsilon_m$ (2)

Where, the dummy variables are defined as:

$Summer\ month = 1$ if the return is from a month during the period May-October, and 0 otherwise.

$Significant\ month = 1$ if the return is from a month that had a significant value ($p<0,05$) in the output from regression (1), and 0 otherwise.

6.1.2. Seasonal Effect

The next step in determining the presence of the Sell in May effect in S&P 500 is to calculate the returns of the 6-month long "summer" and "winter" seasons. By establishing the simple price returns of the 6-month periods, we can assert the index's performance per each of the seasons in question. The simple returns are calculated in the same manner as above, however here r_t is the return for the 6-month season of period t, p_t is the closing price for the period, and p_{t-1} is the closing price for the period previous of t. Only 6-month periods of interest are "summer" (May-October) and "winter" (November-April).

After calculating the price return for each individual period from 1928 to 2024 a dummy variable is created to capture the seasonal category the observed period falls into. Using "winter" as the benchmark season, the regression was structured as follows:

$R_t = \delta_1 + \delta_2 Summer + \varepsilon_t$ (3)

Here, R_t denotes the return for the season year t, δ_1 estimates the average return for the "winter" period and δ_2 gives the effect of the summer.

$Summer = 1$ if the return is observed for April 30th to October 31st of any year and equal to zero if otherwise.

6.2. Risk Premium

6.2.1. Monthly Risk-Free Return

By using the monthly discount rate for a 3-month treasury bill, we calculate the risk-free return for each month since January 1954. The discount rate is at what percentage discount one can purchase the treasury obligation; however, the discount rate represents the discount

for an asset with the maturity of a year (360 days as a standard). The price as a decimal of the treasury bill yield was established using a calculation provided by the US treasury department.[22]

In this case we use 30 days to maturity for every month with the reason of simplicity and with the justification of the minor effect of the 1–2-day error it occasionally has. Since the rates are data from a 3-month treasury bill, it does not have 30 days until maturity, in practice the obligation is claimed after 90 days. However, in theory this yields the same return as using a 4-week treasury bill since the discount rates for all treasury bills, no matter the days to maturity, are approximately perfectly correlated. The decision of assets with 3-month maturity is, as explained in the data section, because of data limitations.

6.2.2 S&P 500's Risk Premium

To determine the risk premium for the S&P 500 market, we estimate the difference of the market return and the risk-free return. Since the risk-free returns for each month were previously calculated, we need to establish all the 6-month periods' risk-free return. In practice with a 3-month treasury bill, this must be done through the purchase of it every quarter of the year, split up into the winter and summer months. However, in theory, and for the reason of creating a fair average of the discount rate, we compound the monthly risk-free rates into six-month periods. With the risk-free return for each of the periods since 1954 we can determine each 6-month season's risk premium.

In order to investigate the differences of the risk premium between the summer and the winter, the following regression it set up:

$$Risk\ premium_t = \phi_0 + \phi_1 Summer\ + \varepsilon_t \quad (4)$$

Where *Risk premium*$_t$ is the risk premium for period t. The dummy variable is defined the same as in regression (3).

[22] United States Department of the Treasury. (2004). *Treasury Calculation Examples*. Treasury Direct. Retrieved May 13, 2024, https://www.treasurydirect.gov/instit/annceresult/press/preanre/2004/ofcalc6decbill.pdf.

If a month is suspected to be the cause of the divergence in the risk premiums, we run a regression controlling for that certain month. The regression uses monthly risk premiums since 1954 and has the winter months as a benchmark group. While controlling for the summer months and the certain month in question we can assert if the summer months actually have a lower risk premium, or if the specific month is the cause for the gap. The regression is structured as follows:

$$Risk\ premium_t = \gamma_0 + \gamma_1 Summer\ month + \gamma_2 Significant\ month + \varepsilon_t \quad (5)$$

Here, *Risk premium*$_t$ is the value for month *t*, and the dummy variables are defined the same as in regression (2).

6.3 Portfolios

6.3.1 Holding Period Returns

To show the findings in "practice", we compute the returns of the portfolios. By using 30-year investment horizons and calculating the holding period return (HPR), we can visualize the historical differences in returns the portfolios yield for a realistic long-term investment.

The first step is to calculate the return of our benchmark portfolio, which simply consists of holding the S&P500 for 30 years. The returns of the first portfolio are calculated through compounding the monthly returns for 30 years. This is done for every year, with the first period being January 1954 to January 1984, and the last being January 1994 to January 2024. This is important as the results will show the changes in portfolio performance over time.

The next portfolio holds the S&P 500 during the winter periods and rotates to a risk-free asset during the summer periods, denoted as the Sell in May (SiM) portfolio. This is done with a 30-year horizon for every year since 1954, just as the benchmark portfolio. The creation of this portfolio has the aim of visualizing the strategy in practice in order to test the findings of this study, thus it must be more realistically calculated. Therefore, as previously explained, a 3-month treasury bill is "purchased" using the discount rate of May and one using August's, with a 90-day maturity. Determining the risk-free return during the summer is therefore done through compounding the 2 specific 3-month treasury bills' returns. Note that the following

calculation however assumes transaction costs to be non-existent, therefore the results do not reflect reality entirely. The calculation proceeds through compounding each year:

$$R_t^{SiM\ Portfolio} = \prod_t^{t+29} (1 + r_t^{SiM\ Portfolio}) - 1$$

Here, R_t is the 30-year HPR starting year t and r_t is the Sell in May portfolios return for year t. Just as the calculation for the S&P 500's 30-year HPRs, this is done starting from every year from 1954 to 1994.

6.3.2 Third portfolio

If the case were to be that a month is suspected to be a cause behind the possible Sell in May effect, we create a third portfolio. This portfolio hypothetically divests from the S&P 500 and rotates to risk-free asset only during the month in question. By creating this portfolio, we can observe how much this month's rotation affects the Sell in May portfolio. The calculation of this portfolio's returns is done in the same manner as above, however using the risk-free yield of a 3-month treasury bill with a theoretical 30-days to maturity. As explained previously, this is not realistic as one cannot claim a 90-day treasury bill after 30 days, but in theory it yields the same return as a 1-month treasury bill.

6.3.3 Geometric Mean Returns

We use the geometric average returns of the portfolios to get the time weighted average returns. This gives the average yearly return of each portfolio from 1954 until 2024. By compounding each portfolio's yearly return we can acquire a summary measure for their yearly performance. The geometric average provides insights that are volatility adjusted and time weighted, therefore a valuable analysis tool for long term investments and portfolio comparison[23]. This is calculated through:

$$\overline{R}_G^{Portfolio\ n} = [\prod_{t=1954}^{2023} (1 + R_t^{Portfolio\ n})]^{\frac{1}{70}} - 1$$

where R_G denotes the geometric average yearly return for portfolio n.

[23] McCulloch, B. W. (2003). Geometric Return and Portfolio Analysis. *SSRN Electronic Journal*.

7. Empirical Results

7.1. Monthly Effects

The results of our first regression (1) are given by Table 1. The second column gives us the OLS predicted difference in return of each month compared to the January and the p-value. From the table we can see that January had an estimated return of 1,19% with a p-value of 0,015 and that September had a predicted difference of -2,20 % with a p-value of 0,001. These two months are the only ones with significant p-values at the significance level of 5% and are highlighted in Figure 1, showing the OLS predicted return of each month.

Table 1

Variable	Effect on return	(2)
Constant	0,0119 ** (0,015)	0,0119 ** (0,015)
Febuary	-0,012* (0,074)	
March	-0,005 (0,485)	
April	-0,000 (0,978)	
May	-0,011 (0,109)	
June	-0,005 (0,471)	
July	0,003 (0,668)	
August	-0,008 (0,668)	
September	-0,022*** (0,001)	-0,022*** (0,001)

Table 1 - Continued

Variable	Effect on return	(2)
October	-0,005 (0,465)	
November	-0,002 (0,748)	
December	0,001 (0,849)	
Observations	1155	
Overall R^2	0,019	

1. The p-values are in parenthesis.
2. *, **, *** denotes significance at the 10%, 5%, ≤1% level, respectively.
3. The significant values are highlighted in the third column.
4. The constant represents the benchmark group, in this case January.

Figure 1 gives the predicted return for each month, hence calculated through adding the constant to each month's effect. Note that only January and September are statistically significant values, thus the green highlight. This means that the other month's predicted returns are less relevant since the observations are relatively volatile and inconsistent.

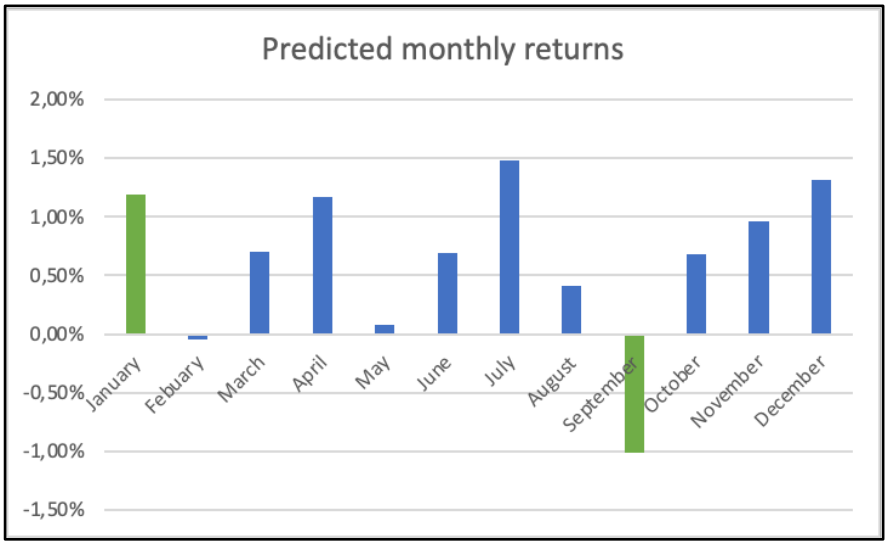

Fig. 1

7.2. January Effect & September Effect

Since the results from regression (1) indicate a significantly positive predicted return for January, we run regression (2) controlling for the specific month. In Table 2 we observe the summer months' effect in contrast to winter months. The prediction gives the effect of -0,49% with a p-value of 0,047. The estimated difference between the winter months' and January's return is -0,28% with a p-value of 0,529, thus insignificant. The January effect can therefore be ruled out as a cause for the divergence in seasonal returns.

Table 2

Variable	Effect on return	(2)
Constant	0,011*** (0,000)	0,011*** (0,000)
Summer months	-0,005** (0,047)	-0,005** (0,047)
January	-0,003 (0,529)	
Observations	1155	
Overall R^2	0,320	

1. The p-values are in parenthesis.
2. *, **, *** denotes significance at the 10%, 5%, ≤1% level, respectively.
3. The significant values are highlighted in the third column.
4. The constant represents the benchmark group, in this case the winter months.

Like January, we observe a significant predicted return for September in regression (1). For that same reason, we run regression (2) again but now controlling for September. The results are presented in Table 3, and the summer months' effect is no longer significant at a 5% level. September however has the value of -1,02% and a p-value of 0,021 thus remaining significant. As the effect for summer months is no longer significant, September is suspected to be a possible cause behind the Sell in May effect.

Table 3

Variable	Effect on return	(2)
Constant	0,010*** (0,000)	0,010*** (0,000)
Summer months	-0,003 (0,267)	
September	-0,010** (0,021)	-0,010** (0,021)
Observations	1155	
Overall R^2	0,320	

1. The p-values are in parenthesis.
2. *, **, *** denotes significance at the 10%, 5%, ≤1% level, respectively.
3. The significant values are highlighted in the third column.
4. The constant represents the benchmark group, in this case the winter months.

7.3. The Sell in May Effect & The Risk Premiums

Determining each season's risk premium since the year 1955 gives the results plotted in Figure 2. The 3D bar-chart shows the difference between the return of the S&P 500 and the risk-free return of each 6-month period, with color indications of summer and winter seasons. By simply observing Figure 2, one can establish that the risk premium tends to be higher during the winter periods in comparison with the summer.

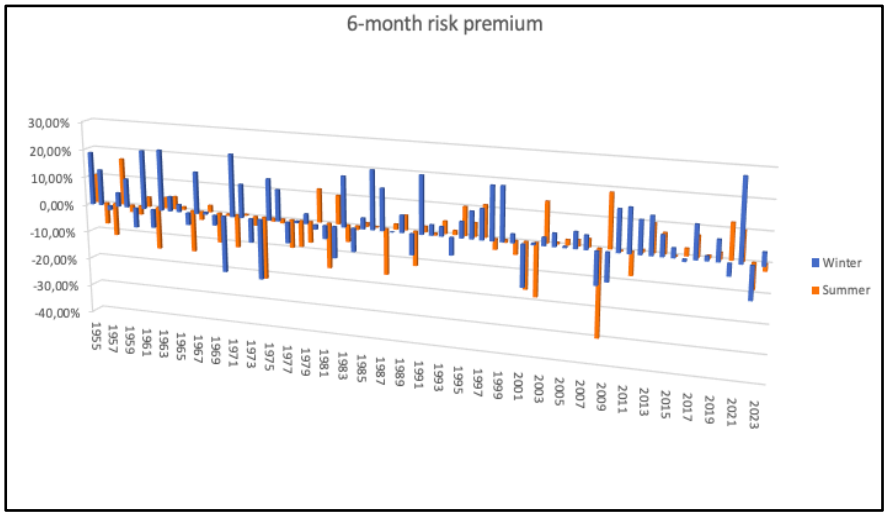

Fig. 2

Regression (3) estimates the effect of the two periods, winter (November-April) and summer (May-October). The results given in Table 4 show that the average return during the winter period is 5,5%, and that the effect of the summer is -2,9%. The predicted effect of the winter is significant with a p-value of approximately zero, and the predicted difference in return for the summer is significant at the 10% level. Note that the p-value of the summer coefficient is 0,055 and therefore very close to the 5% significance level.

Table 4 also shows the results from regression (4). This regression gives the effect of each season on the risk premium with the winter period as a benchmark group. The intercept has a value of 4,34% with the rounded p-value of 0,000. The predicted effect for the summer periods has a value of -5,32% with a p-value of 0,002, which is significant even at a 1% significance-level. This result indicates that the average risk premium for May-October is in fact negative, meaning that the risk-free rate tends to yield a one-percent higher return than the S&P 500 during summer seasons.

Table 4

Variable	Effect on return	Effect on risk premium
Constant	0,055*** (0,000)	0,043*** (0,000)
Summer	-0,029* (0,055)	-0,053*** (0,002)
Observations	192	139
Overall R^2	0,019	0,066

1. The p-values are in parenthesis.
2. *, **, *** denotes significance at the 10%, 5%, ≤1% level, respectively.
3. The constant represents the benchmark group, in this case the winter periods.

7.4. The September Effect & the Risk Premiums

Considering the discovery that September's poor market performance may be a cause for the divergence in seasonal returns, an additional regression (5) is run using the monthly risk premiums and the results are presented in Table 5. The summer coefficient has a value of -0,679%. The p-value is 0,027 and therefore significant at the 5% level. The coefficient controlling for September has a predicted value of -1,309% and significant at the 5% level as the p-value is 0,019.

Table 5

Variable	Effect on risk premium
Constant	0,008***
	(0,000)
Summer months	-0,006**
	(0,026)
September	-0,013**
	(0,019)
Observations	843
Overall R^2	0,018

1. The p-values are in parenthesis.
2. *, **, *** denotes significance at the 10%, 5%, ≤1% level, respectively.
3. The constant represents the benchmark group, in this case the winter months.

7.5. 30-year Holding Period Returns

Figure 3 presents the return of S&P 500, a risk-free asset and the Sell in May portfolio (SiM) with 30-year horizons. Additionally, because of the findings that the low returns of September may be a reason for the lower returns during the summer period, a third portfolio was created, as defined in the methodology section, and is denoted as the September Effect portfolio (SE). This portfolio rotates to the same risk-free asset only during the month of September. The SiM portfolio beat the index every period until 1990. From then on, the portfolio starts to underperform the S&P 500 but not by a large margin. Note that the SiM portfolio has a lower risk profile than the S&P 500 and the returns have not been adjusted for risk. During many of the later holding periods the SE portfolio does however outperform the SiM portfolio.

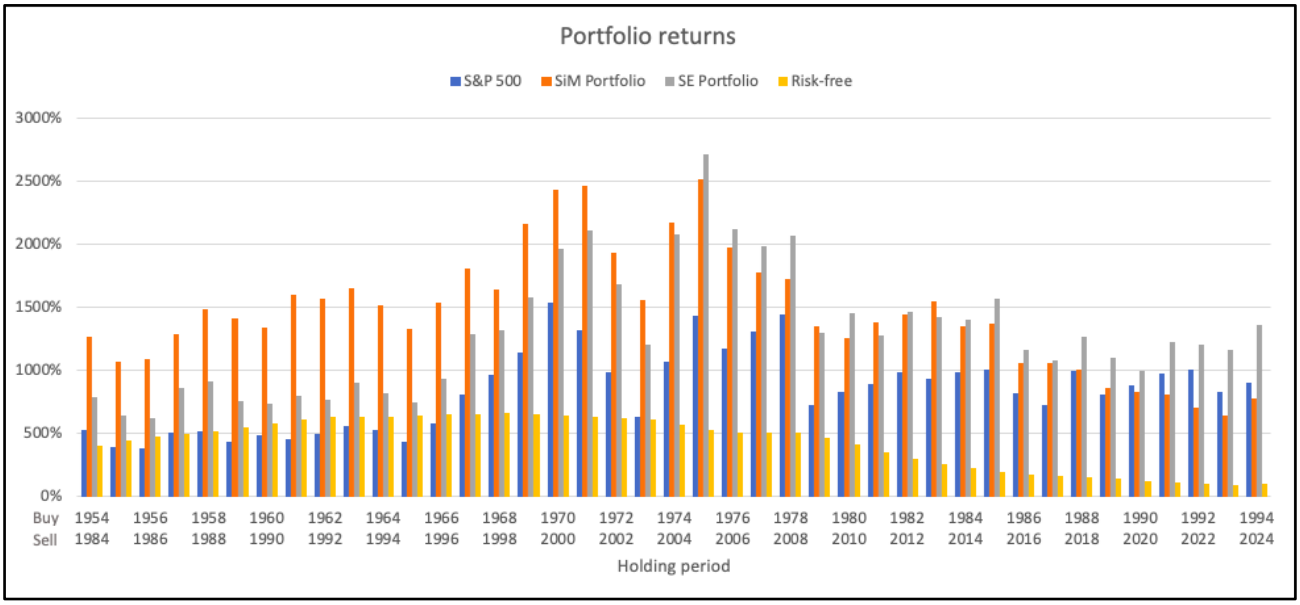

Fig. 3

7.6. Geometric Means and Returns

We also compared the portfolio over the entire period from 1954 until 2024. The total compounded returns are shown in Figure 4 while the annual geometric average return of each portfolio is shown in Table 6. We clearly see that the SiM portfolio has had a higher average return than the S&P 500 and outperformed it in the long run. The SE portfolio outperforms the SiM portfolio only from 2021 onwards although it has a higher annual geometric average. A more detailed view of the results plotted in Figure 4 is given by Table 7 (appendix).

Table 6

Portfolio	S&P 500	SiM Portfolio	SE Portfolio	Risk free
Geometric mean	7,73%	8,82%	9,11%	4,27%

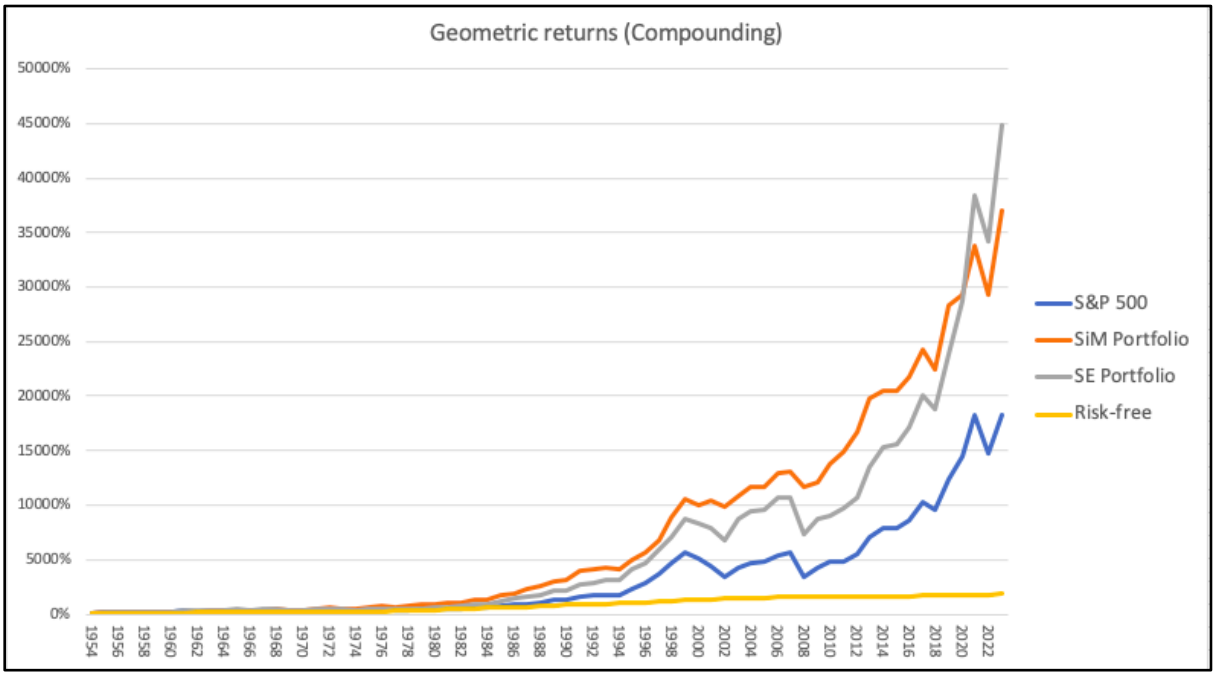
Geometric returns (Compounding)
50000%
45000%
40000%
35000%
30000%
25000%
20000%
15000%
10000%
5000%
0%
1954
1956
1958
1960
1962
1964
1966
1968
1970
1972
1974
1976
1978
1980
1982
1984
1986
1988
1990
1992
1994
1996
1998
2000
2002
2004
2006
2008
2010
2012
2014
2016
2018
2020
2022
S&P 500
SiM Portfolio
SE Portfolio
Risk-free

Fig. 4

8. Discussion

8.1. The Sell in May Effect in the S&P 500

In regression (3) we use an OLS estimator to estimate whether the summer months had a statistically significant difference in return compared to the winter months. The results from the regression are displayed in Table 4 and support the notion that the Sell in May effect occurs in the S&P 500. When controlling for January we find that the Sell in May effect cannot be explained by higher returns in January alone. This contradicts the findings of Bouman and Jacobsen (2002), stating that the Sell in May effect in the US can be explained by the January effect. However, it aligns with the findings of other articles reviewed in Auer and Degenhardt's paper (2018) on the subject.

One surprising finding from our regressions is the statistically significant negative return of September. When controlling for September, the Sell in May effect does not show statistical significance. This indicates that September might be causing the Sell in May effect in the S&P 500, and after some further research we learned that this is another anomaly, commonly known as the “September effect”. Except for January it’s the only month for which returns have been statistically significant. Most economists and market specialists seem to discount the existence of the September effect; however, our data seems to prove otherwise, at least when looking at the S&P 500 over the last 96 years. Our results are however bolstered by the utilization of "fenced" data, consequently diminishing the impact of stock market crashes on the month in which they occur.

Zhang and Jacobsen (2015) conducted a study on whether monthly seasonals are real. They look at over 300 years of UK stock returns and found that monthly anomalies often disappear when a time series increases. One potential “flaw” in our analysis could therefore be the fact that we only have 96 years of data. In their analysis of the UK stock market for instance, Zhang and Jacobsen (2015) find that whether an anomaly exists or not depends on the chosen sample period and length.[24]

[24] Zhang, C. Y., & Jacobsen, B. (2013). Are Monthly Seasonals Real? A Three Century Perspective. Review of Finance, 17(5)

8.2. The Market Efficiency of the S&P 500

The efficient market hypothesis states that for an investment to be able to yield a higher return it must be risker. Since all available information is incorporated into the price of the asset, it is under the assumption that the EMH holds impossible to consistently beat the market through asset selection or market timing.[25]

When simply observing Figure 2, it is evident that the risk premium of the S&P 500 is frequently negative during the summer, an attribute no volatile asset should possess. Figure 2 alone, the plotted risk premiums per season, indicate that a portfolio rotation to a risk-free asset each summer season would prove to be a more profitable strategy. Table 4, presenting the results from regression (4), confirms this indication with a significant result of a negative average risk premium during the summer. The risk premiums during the summer periods are predicted to be 5,32% lower than the winter seasons, of which predicted to be 4,34%. This result strongly suggests that even investing in a treasury bill, taking on zero risk, during the summer is more profitable than risking capital in the market year-round.

To test these findings in “practice” the two portfolios were created, and their holding period return plotted in Figure 3. Here it is evident that the strategy of divesting during the summer has been a consistent winner in contrast to keeping capital in the S&P 500. Through the creation of these portfolios, the strategy’s performance and the magnitude of the difference in returns can be visualized. The portfolio using the strategy beats the index every instance up until the portfolio created 1990, where in the last four 30-year periods it appears to be a losing strategy. What is important to note is that transaction costs are ignored, and as explained in the “data" section the returns of the S&P 500 do not include dividends, hence the numbers are not entirely accurate to reality. However, the observed marginal differences in the yield of the two portfolios are large enough that one can still assume that the strategy has consistently outperformed the index almost all the studied years.

Moving towards the last 10 observations in Figure 3 the gap between the returns start to close and invert. Viewing Figure 2, one can see that the risk premiums for years 2010-2024 have had a relatively high value, for both the summers and the winters, and barely experienced a

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

negative value. This could be explained by the stock markets and the S&P 500's improved performance during these years but also by the extremely low returns of risk-free assets. Returns on assets such as treasury obligations are dependent on the federal interest rate as it is a "loan", and when interest rates were kept extremely low during the recovery of the great recession[26], the returns on treasury bills were at an all-time low, in essence zero. Therefore, the 30-year portfolios that extend over the periods in question are somewhat expected to have a lower yield than the market index. Since the risk premium cannot be negative these periods unless holding the market index yields a loss, it is not surprising that the Sell in May portfolio underperforms the index.

Observing the geometric returns in Figure 4, those compounded for each portfolio since 1954, one could establish that the SiM portfolio clearly is the superior strategy in comparison to investing in the market. Although the magnitude of the difference in returns are extremely high, one must understand that with yearly compounding since 1954 minor differences in yearly returns have a great effect and since this is a 70-year period it is not a realistic investment horizon. However, observing the geometric averages in Table 6, we can clearly see that the SiM portfolio has a larger average yearly return. Even though the difference is approximately 1,1%, the difference in the long run is visible through the geometric returns in Figure 4.

Returning to the question if the Efficient Market Hypothesis holds for the S&P 500, the answer cannot be answered by a simple yes or no. None of this research in this study focuses on the fairness, accuracy or the incorporated information of asset prices. Instead, it aims to disprove key assumptions of the theory. One assumption that is vital for EMH to hold is that for an asset to be able to yield increased returns, the asset must be riskier. There may be many alternative assets that prove more profitable to invest in during the summer, a certain stock or industry for example, but here the risk that the investor acquires may be higher or even the same. The decision to use risk premiums and "invest" in treasury bills in SiM portfolio was for simplicity as there is no need to calculate the risk, it is simply nonexistent. With the results that SiM portfolio consistently outperformed the index, the assumption that the asset, or portfolio, must be riskier to yield higher returns is disproved.

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[26] Weinberg, J. (2013, November 22). *The Great Recession and Its Aftermath*. Federal Reserve History; Federal Reserve Bank of Richmond.

Another assumption of the Efficient Market Hypothesis that our results challenge is that the market cannot be beaten through timing or asset-selection. If the EMH holds, since all available information is incorporated in the price, the assets are priced accurately. It should therefore not be possible to consistently yield returns through rotating the portfolio at certain times as a recurring movement should be predicted and reflected in the asset's price. The results of this study says otherwise. Through precisely rotating the exact same period every year for 30 years the market will be beaten, at least for 88% percent of the time. The remaining 12% that the SiM portfolio is not superior, as explained previously, is mostly because of the record-low interest rates. As the market index could be beaten so consistently through the mentioned methods of asset selection and timing, this key assumption of the EMH has also been disproven for the S&P 500. For this to be true, no careful selection of assets through any analysis had to be done. Since regression (4) predicts a negative risk premium for the summer seasons, even the simplest form of asset-selection, a risk-free obligation, could beat the market.

For the weak form of the Efficient Market Hypothesis to hold, all of the historical prices, movements and reactions of an asset is incorporated in the price. This renders a technical analysis ineffective since anything learned through observing the assets history is already integrated and reflected by the current price. Since this study is entirely based on historical data, it suggests that not even weak form holds for the S&P 500. Through analyzing the historical price movements of the index, it is possible to learn various patterns that, with the knowledge of their presence, can be used to yield abnormal returns. The fact that the S&P 500 market index has this attribute, strongly suggests that not even the weak form of market efficiency holds. We therefore conclude that the S&P 500 is an inefficient market, at least according to Fama's Efficient Market Hypothesis.

8.3. The September Effect or the Sell in May Effect?

The findings presented in Table 3 suggest that the poor performance of the S&P 500 during September may be a reason for the large gap in estimated returns during the summer and winter periods. The September effect, a known but rather disregarded anomaly, according to our study's findings seems to be present in the S&P 500.

Due to this unexpected finding, additional research was made regarding the September effect. The anomaly is studied in various markets across 47 different countries by Fang, Lin and Shao (2017).[27] They find the presence of the September effect in a majority of the studied countries, including the U.S where the S&P 500 is based. The underlying reason that the anomaly exists cannot be pinpointed, some hypothesize tax-loss harvesting in the manner of the turn-of-the-year effect, however Fang, Lin and Shao investigate the post-school holiday's effect on the stock market. Their findings suggest that investors are more inactive and slower to react to news during the school vacations, thus negative news are incorporated into the price with a delay, inevitably affecting September. However, they also acknowledge that September's poor performance could just be a statistical artifact and a product of the many random aspects of financial markets. Although it is highly unlikely that "randomness" produces such a significant result, it is important to keep in mind as it is a statistical probability. [28]

The findings in our study supports the presence of the September effect in the S&P 500. Table 1 and Figure 1 presents it as the significantly worst month of the year. Due to this finding, we test whether the later results, that the summer seasons have a significantly worse performance than the winter seasons, could entirely depend on September's returns dragging the 6-month period down.

Table 3 presents the results from running regression (2) while controlling for September. The results gathered from this table alone suggests that September indeed is the cause for the summer months performing worse than the winter months. Since the difference in predicted return between a summer month and a winter month is no longer significant, while September is significantly negative, one can assume that this is the case. We can therefore not establish the fact that all the summer months are estimated to yield lower returns than all the winter months. While investigating the summer months as a whole unit, the period return was predicted as 2,89% lower than the winter periods as presented in Table 4. With a p-value of 0,055 it is statistically significant at a 10% level, however extremely close to satisfying a 5% significance level. This result supports the Sell in May effect's presence since in theory the anomaly is defined as the entire period yielding lower results than the winter period. From

[27] Fang, L., Lin, C., & Shao, Y. (2017). School Holidays and Stock Market Seasonality. *Financial Management*, *47*(1).
[28] Ibid.

these results we can therefore confirm that the summer period yields lower returns than the winter periods at a 10% significance level.

Due to the uncertainty of the September effect's involvement in the seasonal divergence we investigate the monthly risk premiums, the results are observed in Table 5. Note that in contrast to the previous results discussed under this subsection, these findings are based on later data starting 1954. What can be learned from the findings in Table 5 is that the risk premium during summer months is no longer estimated as negative, however still much lower than during the winter months. This value, along with the one controlling for September are significant at the 5% level. Observing Table 5 one can therefore see that the summer months do have a significantly lower risk premium than the winter months, even when controlling for September. Although the coefficient for September is strongly negative, we can still conclude that the other months collectively have a lower predicted risk premium than the winter months.

The third portfolio created, the September Effect (SE) portfolio, rotates to a risk-free asset only during September. By directly comparing it to holding the S&P 500 with 30-year horizons, this portfolio yields higher returns in every instance. This means that historically September has mostly had negative risk premiums in the S&P 500. When comparing the SE portfolio to the SiM portfolio, it yields lower returns in more than half of the instances, suggesting that it is the superior strategy, however during later starting years it has been the underperformer. The later years can, as previously stated, be explained by the low interest rates in combination with the improved performance of the S&P 500. Observing the geometrical returns in Figure 4, compounded since 1954, the SE portfolio is the superior one, but only overtaking the SiM portfolio year 2021. However, viewing Table 6 one can see that the yearly geometric average returns for the SE portfolio is higher than for the SiM. This finding directly contradicts that that SiM is the superior strategy and supports the suspicion that the September effect could be the cause for lower returns during the summer.

Returning to the question if the Sell in May effect is present in the S&P 500 the answer, based on the findings in this study is yes. Since the Sell in May effect is concerning the entire seasons, we can conclude that the market experiences this effect, the summer periods yield a significantly lower return than the winter periods.

When it comes to the question if September is the cause of the divergence, there is a less straightforward answer. One can argue from the results in Table 3 that it is the sole cause since controlling for it causes the summer months' lower returns to lose significance. However, when examining the conclusions drawn from the results in the risk premium section, it seems that even when controlling for September, the summer months have a collectively lower predicted risk premium than the winter months anyway.

The 30-year HPRs also suggest that it is not only September that has a lower risk premium. If September was the only month during the summer with the attribute of a consistently low risk premium, then the SiM portfolio would not be able to outperform SE portfolio the majority of the instances. However, note that the risk premiums are also dependent on the movements of the risk-free asset's discount rate, not only the various months' yield. But since only holding the risk-free asset for 30 years barely ever outperforms the S&P 500, we can still assume the previous conclusion to be true, that September is not the only month during the summer to have negative risk premiums. The geometric returns and average support the claim that the September effect is the cause as the SE portfolio yields higher returns, at least in the later years. One must however consider the low interest rates keeping the risk premium extremely low, hence a portfolio holding treasury bills 6 months of the year will inevitably yield lower returns than the stock market.

To conclude this section, September evidently is a cause for the magnitude of the divergence, since it does "drag the average down" and the September effect is definitely present in the market. However, we determine it to rather be a large part of the divergence, not the sole cause of it, therefore we conclude that both of the anomalies in question exist in the S&P 500.

9. Conclusion

The analysis conducted in this study provides compelling evidence that the Sell in May effect is present in the S&P 500. Through the usage of OLS regressions, we assert that the summer period (May-October) tends to yield lower returns than the winter period (November-April). Contradicting the Bouman and Jacobsen study (2002), the January effect is not responsible for the divergence in returns between the summer and winter seasons.

One intriguing finding made in this study however is that in the S&P 500 September has been observed to have significant and strong negative returns. This is due to another market calendar anomaly known as the September effect. As the month had this effect, it was suspected that it could be the cause for the lower returns during the summer. Controlling for September when regressing monthly returns results in the summer having an insignificant value, therefore supporting the conjecture. Further results when analyzing risk premiums and portfolios does however contradict this.

Through portfolio simulations and analyses on the risk premiums of the S&P 500 we establish that rotating the portfolio to even a risk-free asset during the summer would have consistently yielded higher returns than the index. Calculating the geometric average of the portfolios since 1954 further supports this claim. The results of this study therefore indicate a failure of the Efficient Market Hypothesis through disproving many of the assumptions that are required for it to hold. For the weak form of efficiency, one should not be able to use technical analyses and asset selection to yield higher returns, however since our research finds repeating patterns in the S&P 500 that can be exploited, we determine it does not hold.

Overall, our study concludes that the Sell in May effect is present in the S&P 500. We recognize the September effect's additional presence and its influence on the magnitude of the divergence, however rather as a large part of it and not the sole cause. With the presence of the two anomalies and being able to historically yield higher returns due to exploiting them, we conclude that the Efficient Market Hypothesis does not hold for the S&P 500.

10. References

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11. Appendix

Table 7 describes the data used in Figure 4, the compounded returns of each portfolio:

Table 7

Year	S&P 500	Sell in May Portfolio	SE Portfolio	Risk free
1954	138%	124%	129%	101%
1955	174%	141%	161%	103%
1956	179%	156%	174%	105%
1957	153%	151%	159%	109%
1958	212%	177%	210%	111%
1959	230%	196%	240%	115%
1960	223%	196%	248%	118%
1961	274%	232%	312%	121%
1962	242%	240%	290%	124%
1963	288%	273%	349%	128%
1964	325%	294%	385%	133%
1965	354%	315%	408%	138%
1966	308%	318%	359%	145%
1967	370%	390%	418%	151%
1968	398%	407%	436%	160%
1969	353%	398%	398%	171%
1970	353%	403%	388%	182%
1971	391%	504%	434%	190%

Table 7 - Continued

1972	453%	573%	507%	198%
1973	374%	485%	405%	212%
1974	263%	435%	325%	229%
1975	346%	577%	445%	243%

1976	412%	697%	521%	255%
1977	365%	674%	464%	269%
1978	369%	732%	476%	290%
1979	414%	862%	539%	321%
1980	521%	948%	668%	360%
1981	470%	1007%	645%	413%
1982	539%	1065%	739%	458%
1983	632%	1312%	864%	499%
1984	641%	1349%	887%	549%
1985	810%	1677%	1168%	591%
1986	929%	1912%	1470%	627%
1987	947%	2301%	1545%	664%
1988	1065%	2503%	1680%	711%
1989	1355%	3018%	2167%	771%
1990	1266%	3190%	2147%	830%
1991	1599%	3962%	2776%	875%
1992	1671%	4173%	2880%	906%
1993	1789%	4267%	3122%	933%
1994	1761%	4093%	3171%	974%
1995	2362%	4997%	4107%	1029%
1996	2840%	5719%	4705%	1082%
1997	3721%	6736%	5877%	1138%
1998	4713%	8850%	7032%	1194%

Table 7 - Continued

1999	5634%	10601%	8686%	1251%
2000	5062%	9969%	8289%	1326%
2001	4402%	10410%	7864%	1370%
2002	3374%	9783%	6780%	1392%

2003	4263%	10845%	8680%	1406%
2004	4647%	11650%	9385%	1427%
2005	4786%	11681%	9628%	1473%
2006	5438%	12932%	10720%	1545%
2007	5630%	13123%	10748%	1613%
2008	3463%	11635%	7277%	1633%
2009	4276%	12108%	8675%	1636%
2010	4822%	13706%	8998%	1638%
2011	4822%	14918%	9693%	1639%
2012	5469%	16756%	10733%	1641%
2013	7087%	19754%	13509%	1641%
2014	7895%	20545%	15285%	1642%
2015	7837%	20461%	15586%	1643%
2016	8584%	21797%	17097%	1648%
2017	10252%	24210%	20048%	1664%
2018	9612%	22381%	18751%	1697%
2019	12388%	28285%	23794%	1732%
2020	14402%	29301%	28795%	1737%
2021	18275%	33762%	38365%	1738%
2022	14722%	29255%	34181%	1776%
2023	18289%	37075%	44837%	1868%

Table 8 describes the details regarding the revised monthly returns, of which were detected as outliers:

Table 8

Month-Year	Observed return	Revised return
Oct-29	-19,9%	-14,4%
Jun-30	-16,5%	-14,4%
Sep-31	-29,9%	-14,4%
Dec-31	-14,5%	-14,4%
Apr-32	-20,2%	-14,4%
May-32	-23,3%	-14,4%
Jul-32	37,7%	16,1%
Aug-32	37,5%	16,1%
Feb-33	-18,4%	-14,4%
Apr-33	42,2%	16,1%
Mar-38	-25,0%	-14,4%
Jun-38	24,7%	16,1%
Sep-39	16,5%	16,1%
May-40	-24,0%	-14,4%
Oct-74	16,3%	16,1%
Oct-87	-21,8%	-14,4%
Aug-98	-14,6%	-14,4%
Oct-08	-16,9%	-14,4%
Observations	18	
k	1,5	
s_{H-L}	5,55%	
Upper fence	16,1%	
Lower fence	-14,40%	

Table 9 describes the details regarding the revised seasonal returns, of which were detected as outliers:

Table 9

Season - Year	Observed return	Revised return
Winter-30	-32,0%	-16,1%
Summer-31	-30,2%	-16,1%
Winter-32	-44,6%	-16,1%
Summer-35	34,3%	26,0%
Summer-37	-24,8%	-16,1%
Winter-38	-21,5%	-16,1%
Summer-38	35,8%	26,0%
Winter-39	-17,1%	-16,1%
Winter-42	-19,4%	-16,1%
Summer-46	-20,9%	-16,1%
Winter-70	-16,2%	-16,1%
Winter-74	-16,6%	-16,1%
Summer-74	-18,2%	-16,1%
Summer-02	-17,8%	-16,1%
Summer-08	-30,1%	-16,1%
Winter-21	27,9%	26,0%
Observations	16	
k	1,5	
s_{H-L}	14,20%	
Upper fence	26%	
Lower fence	-16,10%	

1. Since the winter period stretches over two different years, the appointed one is the year the winter ends. Ex: “Winter-30” is Nov-1929 to Apr-1930.