DECEMBER AND JANUARY EFFECT AND VOLATILITY IN THE UNITED STATES STOCK MARKETS

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ABSTRACT

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Abstract

Financial markets have been researched to encounter several seasonal patterns, which are called anomalies. The January effect is the most studied anomaly at the monthly level, and this research studies it too. The Efficient Market hypothesis suggests that past stock prices should not have predictive power on future stock prices, and the January effect is a proof against it. Since the January effect was found, it has gone through intense empirical investigations with various methods causing conflicting results. In most of the research papers, January effect has been found to be in shares of the companies having the smallest market value. The three commonly suggested possible explanatory factors behind the January effect are the Tax-Loss-Selling hypothesis, the Information hypothesis, and the Portfolio Rebalancing hypothesis. Although in several researches the January effect is still observed, it has been stated to be diminishing or even disappearing.

In this research a review of previous literature is done, although regarding the impact of volatility on the January effect, it is somewhat limited by the small number of research papers on this subject. In the literature either Markov regime switching model or a time-series GARCH approach is used as the methodology. Literature, where the latter methodology is used, serve as the basis of this research.

In the empirical part of this research risk being the possible explanatory factor behind the December and January effect in the United States stock markets, with data from years 1926–2021, is studied. The analysis is done by using the multiple linear regression analysis and the GJR-GARCH approach. In addition, the relationship between the January effect and the firm size, is examined.

The results of this research show that when the market value of the companies increases the December effect increases and, on the opposite, when the value decreases the January effect increases. The results also show that a GARCH-in-Mean effect is observed in shares of small market value companies.

Key words
Anomalies, January effect, company size, stock returns, volatility

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Tiivistelmä

Rahoitusmarkkinoiden on tutkittu kohtaavan useita kausittaisuuksia, joita kutsutaan anomalioiksi. Kuukausitasolla tammikuuilmiö on kaikista tutkituin anomalia, ja myös tämä tutkimus keskittyy siihen. Tehokkaiden markkinoiden hypoteesin mukaan aiempien osakekurssien avulla ei pitäisi pystyä ennustamaan tulevia osakekursseja, ja tammikuuilmiö onkin todiste tätä hypoteesia vastaan. Siitä lähtien kun tammikuuilmiö havaittiin ensimmäisen kerran, se on käynyt läpi intensiivisiä empiirisiä tutkimuksia erilaisilla menetelmillä, jotka ovat tuottaneet ristiriitaisia tuloksia. Useimmissa tutkimuksissa tammikuuilmiön on havaittu esiintyvän markkina-arvoltaan pienten yritysten osakkeissa. Kolme yleisimmin ehdotettua mahdollista selittävää tekijää tammikuuilmiölle ovat verohypoteesi, informaatiohypoteesi sekä portfolion uudelleenmuodostamishypoteesi. Vaikka useissa tutkimuksissa havaitaan vieläkin tammikuuilmiötä, sen on todettu pienenevän tai jopa häviävän.

Tässä tutkimuksessa tarkastellaan aiempaa kirjallisuutta, mutta sen laajuutta rajoittaa volatiilisuuden vaikutusta käsittelevien tutkimusten pieni lukumäärä. Tarkastelun kohteena olevassa kirjallisuudessa menetelminä on käytetty joko regiimin muutosmallia tai GARCH-mallia. Kirjallisuus, jossa käytetään jälkimmäistä menetelmää, toimii tämän tutkimuksen perustana.

Tämän tutkimuksen empiirisessä osassa tutkitaan riskin toimimista selittävänä tekijänä joulu- ja tammikuuilmiölle Yhdysvaltojen osakemarkkinoilla vuosien 1926–2021 aineistolla. Analyysi tehdään käyttämällä lineaarista GARCH-mallia. Lisäksi tutkimuksessa tarkastellaan tammikuuilmiön ja yrityskoon välistä suhdetta.

Tämän tutkimuksen tulokset osoittavat, että yrityksen markkina-arvon kasvaessa joulukuuilmiö kasvaa ja markkina-arvon laskiessa tammikuuilmiö kasvaa. Tulokset osoittavat myös, GARCH-in-Mean -ilmiö esiintyy markkina-arvoltaan pienten yritysten osakkeissa.

Asiasanat
Anomaliat, tammikuuilmiö, yrityskoko, osaketuotot, volatiliteetti

Säilytyspaikka
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1 INTRODUCTION

The Efficient Market hypothesis is one of the most studied financial theories. The hypothesis suggests that past stock prices should not have predictive power on future stock prices. Also, security prices should constantly reflect all available information, which is the reason why investors should not be able to generate abnormal profits (Fama, 1970). However, there are numerous challenges to this hypothesis which have been studied. It is broadly known that in the empirical finance, stock returns can encounter seasonal patterns, i.e., anomalies, which is the reason why especially January has been a unique month for investing. It has been observed, that in January, mainly during the two first weeks, the stock returns have been systematically higher than in other months of the year. This observation is called the January effect, and it is a proof against the Efficient Market Hypothesis, especially its weak-form efficiency, just like other seasonalities in the financial markets.

January effect is the most studied anomaly at the monthly level. Wachtel (1942) was the first one to refer to the January effect, and since then it has gone through intense empirical investigations. After the study of Rozeff and Kinney (1976), which was the first one to provide empirical evidence of the January effect in the United States, several researchers have either studied the statistical significance of the January effect or have tried to explain the abnormal stock returns in January. Keim (1983), Reinganum (1983), and Roll (1983) confirmed the previous results and found that the January effect can mainly be associated with small firm stocks, when using US data. Only after the studies done in the early 1980s, the January effect has become popular. Although the January effect has been mainly studied as a phenomenon concerning only stock markets, studies have also been broadened to bond markets and foreign exchange markets, for example. Gultekin and Gultekin (1983) documented a significant January effect outside the US in major industrialised countries and Fama & French (1993) documented January effect in bonds.

Although January effect has been studied widely, the results have been contradicting and researchers have not yet reached an agreement about the explanatory factors behind the January effect. In addition, some results show that January effect occurs only in shares of small market value companies, whereas in others the negative correlation between January returns and company size have not been observed. In the studies of the January effect, several explanations for the abnormally high stock returns have been suggested. The two most notable explanatory factors behind the January effect are the Tax-Loss-Selling hypothesis (Wachtel, 1942) and the Window-Dressing hypothesis (Haugen & Lakonishok, 1988). In the Tax-Loss-Selling hypothesis, investors sell their poorly performing stocks in December and buy them back in January, to gain tax benefits. In essence the Tax-Loss-Selling hypothesis is supported mostly in countries where the tax year is consistent with the calendar year, starting in January and ending in December. (Reinganum, 1983.) In the Window-Dressing hypothesis portfolio managers sell losing stocks in December and buy them back in January, to produce annual reports that do not show holdings of poorly performing stocks (Haugen & Lakonishok, 1988, as cited in Lee at al., 1998). The repurchase of the stocks in the beginning of new year creates the abnormal stock returns observed in January.

January effect has been studied by many different methods, but the most familiar and used method is the dummy variable regression model. Nevertheless, the model has received criticism of for example not considering different market situations such as financial crisis and its impact on the January effect (Floros & Salvador, 2014). In studies of the January effect also non-linear time series models, such as GARCH models, have been introduced in the 21st century.

In GARCH and especially in GARCH-in-Mean approach the impact of possibly higher volatility in the year end is controlled. This gives an opportunity to test by seize groups whether the January effect is caused by higher risk and if it is compensation of that risk. For example, Sun and Tong (2010) used the GARCH approach to test possible link between January effect and market volatility risk.

The empirical part of this master's thesis adapts the Sun and Tong's (2010) research, where they found that the January effect is due to higher risk compensation, not due to risk itself. This research studies the possibility of risk being the explanatory factor behind the December and January effect in the US market using the multiple linear regression analysis and the GJR-GARCH approach. In addition, the relationship of the January effect to firm size is studied. Even though for example development of trading systems, reduction of information costs, and loosening of tax laws have made the financial markets even more efficient, January effect is still observed. When including January effect into the investment strategy, it is possible for investors to generate abnormal profits compared to the level of the risk. This is the reason why January effect is very intriguing research subject.

The structure of this research is as follows: In chapter two the Efficient Market hypothesis and the January effect, as well as the most well-known and acknowledged reasons behind January effect, are presented. Chapter three presents previous literature, where risk is being examined as the explanatory factor behind the January effect. In chapter four the data and methodology of this master's thesis are presented. Chapter five presents the results and analysis based on previous chapters. Chapter six concludes everything and potential research questions for further studies are presented.

2 THEORETICAL FRAMEWORK

2.1 Efficient Market hypothesis

Capital market, in which prices provide accurate signals for resource allocation, is ideal. The assumption in this ideal market, is that security prices constantly fully reflect all available information at any time, whereupon companies can make production-investment decisions and investors can choose from securities that represent ownership of corporate operations. A market in which security prices constantly fully reflect all available information is called efficient market. In the efficient market, trading of securities and all available information is costless to all market participants, and they all agree on the implications of given information's impact on both the given and the future prices. This is not the description of markets met in practise, but the market conditions are still sufficient for market efficiency. (Fama, 1970.)

Studies usually divide market efficiency into three categories. The first one is called weak-form efficiency in which the concern is on how well future returns can be predicted from the past returns. Stock prices reflect the historical data, and investors cannot take advantage of technical analysis to make excess profits, because stock markets do not have memory. Due to this it is impossible to predict stock prices and the future price development follows the random walk. The second one is called a semi-strong-form efficiency and it is concerned with how quickly public information announcements, like stock splits, reflect on the security prices. The third and the last one is called strong-form efficiency in which the concern is on has any investor or group a monopolistic access on information, that is not fully reflected in the market prices. (Fama, 1970.)

The Efficient Market hypothesis (EMH) assumes, that stock prices are unpredictable, because they follow a random walk. Due to this and the other assumption, that security prices should constantly reflect all available information, investors should not be able to generate abnormal profits. If there are high returns in the market, they should only be due to higher risk. (Fama, 1970.) However, there is a remarkable amount of evidence that suggest that some factors can be used in the prediction of future stock prices, which violates the weak-form efficiency. The presence of calendar anomalies or seasonalities in the stock market returns have been a constant theme in the market efficiency literature.

2.2 January effect

The first findings of the anomalies in financial economics and of the January effect were observed already before the EMH, when Wachtel (1942) detected seasonal movements in the stock market returns. The main seasonality was that the stock returns were higher in January than in the other months. The data used was from the Dow Jones Industrial Average (DJIA) and the sample period was from 1927 to 1942, covering 15 years. It was observed that during eleven of the 15 years DJIA index rose 5–10% during January, with was significant. Wachtel gave five possible reasons behind this abnormal rise, but made the analysis only based on the Tax-Loss-Selling hypothesis. (Wachtel, 1942.)

Roseff and Kinney (1976) were the next ones to detect the January effect, while examining occurrence of seasonalities in the New York Stock Exchange (NYSE) during 1904–1974. The sample period was divided into three sub-periods, from 1904 to 1928, from 1929 to 1940, from 1941 to 1974. There was also a sub-period that consisted of years 1904–1928 and years 1941–1974. Examining the data adjusted with autocorrelation, any seasonalities were not found, and it was stated that the method was defective. Seasonalities were found when the return distributions of the months were examined separately with parametric and non-parametric methods. Statistically significant differences in the monthly returns were found in all sub-periods, except in the period from 1929 to 1940. The found seasonality was mostly due to returns that were higher than average in January, which referred to the existence of the January effect. It was stated that in January there also occurred higher risk premiums than in other months. The usage of the NYSE might be the reason behind these results because the index gave the same weight for each of the companies. One of the suggested explanatory factors behind the January effect was the Tax-Loss-Selling hypothesis. (Roseff & Kinney, 1976.)

Keim (1983) was one of the first researchers who detected that higher returns in January were mostly caused by returns in small firm stocks. The data consisted of the NYSE and the American Stock Exchange (AMEX), and the sample period was from 1963 to 1979. The data was divided into 10 different portfolios, based on the market values of the companies. It was found that the relation between abnormal returns and company size was always negative, and the relation was even steeper in January compared to other months. Even during years when bigger companies gained higher risk adjusted returns on average than smaller ones, the relation was still steeper. The result of the study implicated that the January effect is related to the small firm returns, due to the result that over 50% of the higher returns of the small firm stocks were concentrated on January. It was found that around 26% of the abnormal returns took place on the five first trading days of the year and even 11% on the first trading day. It was also found that 50% of the higher returns in January took place on the first trading week of the year. It was stated that the Tax-Loss-Selling hypothesis and Information hypothesis were the explanatory factors behind the January effect. (Keim, 1983.)

Gultekin and Gultekin (1983) were the first ones to prove that the January effect was not limited to the United States only. They examined the seasonalities of the stock markets on the 17 most significant developed countries with market value weighted indices. The sample period was from 1959 to 1979. Both parametric and non-parametric methods were used, and they generated converging results. The results indicated that seasonality occurred at the 10% significance level within 13 countries. With most of the countries the January effect seemed to be even more prominent than what it had been in the US markets. Due to the usage of the market value weighted indices, small companies got smaller value which might have had an impact on the significance of the results. Because significant seasonality did still occur, it implicated that January effect might not just be limited to the small firm stocks. It was suggested that the explanatory factor behind the January effect was the Tax-Loss-Selling hypothesis. (Gultekin and Gultekin, 1983).

2.3 Tax-Loss-Selling hypothesis

The most examined and acknowledged factor behind January effect is the Tax-Loss-Selling hypothesis. According to the Tax-Loss-Selling hypothesis investors have the tendency to sell losing stocks in the end of the tax year to minimize their taxes with the deductible capital loss. In other words, investors want to realise the losses in the end of the year that can be subtracted from other possible returns, creating tax savings for investors. This creates selling pressure to stock markets in the year end. When the tax year has changed, there is buying pressure in markets, as investors return to the desired portfolio compositions. After this the pressure releases and the stock prices go to their equilibrium level during January. (Jones, Pearce & Wilson, 1987.) Especially small firm stocks can be unprofitable, which is the reason why they are for sale in the end of the tax year. This hypothesis supports the view that January effect is associated especially with small firm stocks. (Agnani & Aray, 2011).

In several countries the tax year is consistent with the calendar year, meaning it starts in January and ends in December. Nevertheless, this is not the case with all countries, for example in Australia the tax year ends in June. The Tax-Loss-Selling hypothesis has been widely examined and it has gained support for and against. In some studies, it has been found, for example that in countries, where the tax year is not consistent with the calendar year, stock returns in January are still higher than in other months of the year. Results like this support the view that the Tax-Loss-Selling hypothesis cannot be the only explanatory factor behind January effect. (Jones et al., 1987.)

January effect has also been examined through different time periods, both before and after taxes took effective. For example, in the study of Jones et al.

(1987) it was found that the January effect has already appeared well before income taxation was applied and there were not any significant changes in the effect even after taxes took place. Also results like this do not support the Tax-Loss-Selling hypothesis being the only explanatory factor behind the January effect.

When Gultekin and Gultekin (1983) examined the Tax-Loss-Selling hypothesis as the explanatory factor behind the January effect, in 11 countries out of the 17 studied, the tax year was consistent with the calendar year. For example, in the United Kingdom the tax year ends in April and in Australia it ends in June. Despite this, it was found that in the UK there were significantly high stock returns in January and in April. In Australia there was not found any significant deviations in the stock returns in July. It was stated that there was a connection between abnormal stock returns and the change of the tax year. The Tax-Loss-Selling hypothesis was suggested to be the explanatory factor behind the January effect but not the only factor. (Gultekin & Gultekin, 1983.)

2.4 Information hypothesis

Another well-known and acknowledged reason behind January effect is the Information hypothesis. With several companies the fiscal year is consistent with the calendar year, meaning it starts in January and ends in December. In the stock market, there is uncertainty before accounting information is released, which creates pressure in the markets. When the accounting information is released in January, the uncertainty in the stock markets decreases and stock prices go to their equilibrium level. According to the Information hypothesis, the stock returns in the last month of the fiscal year should be less than the stock returns are in the next month, meaning December stock returns should be less than the next January returns are in the case of January effect. To consider Information hypothesis as a relevant factor explaining January effect, companies should have higher stock returns in January than in December, if their fiscal year is consistent with the calendar year. (Kim, 2006.)

Kim (2006) examined information hypothesis as the explanatory factor behind January effect. The data was constructed from companies, that were listed in the NYSE or in the AMEX during 1972–2003. The companies were divided into 12 different groups based on the ending of the fiscal year. The results showed that despite the company size, the stock returns of only four companies were less in the end of the fiscal year than the returns in next month. It was stated that regardless of the ending month of the fiscal year the stock returns were higher in January than in other months. These results were inconsistent with the Information hypothesis, and they do not support the Information hypothesis being the only explanatory factor behind the January effect. (Kim, 2006.)

2.5 Portfolio Rebalancing hypothesis

According to Portfolio Rebalancing hypothesis institutional investors tend to rebalance their portfolios around the turn of the year. Haugen & Lakonishok (as cited in Lee at al., 1988.) studied, whether the before mentioned behaviour of the portfolio managers is the primary cause behind the January effect in the small firm stocks. They divided their hypothesis into two parts, to the Window-Dressing hypothesis and to the Performance Hedging hypothesis. In the end of the year, according to the Window-Dressing hypothesis, investors sell the higher risk stocks from their portfolios. Usually, these riskier stocks are small firm stocks. After the New Year, the investors potentially repurchase the stocks, which causes higher abnormal returns in January. (Haugen & Lakonishok, 1988, as cited in Lee at al., 1998.)

According to the Performance Hedging hypothesis, when the yearend comes nearer investors sell stocks from their portfolios, which they estimate will not gain value before the yearend. In this way the investors lock the whole year's returns to the level in which they are at the specific moment in the end of the year. After the New Year, investors buy new stocks, which causes higher stock prices in January. Performance Hedging can be seen as a stock return protection, which is due to the investors' desire to maximize their returns. (Lee et al., 1998.)

Ten years later Lee et al. (1998) studied the behaviour of the portfolio managers even more closely, aiming to find out which one of the two hypotheses had more impact on the January effect. The main result confirmed the previous results, that the behaviour of the portfolio managers is the explanatory factor behind the January effect of small firm stocks. It was also found that the results were more due to the behaviour related to the Performance Hedging hypothesis rather than the Window-Dressing hypothesis. (Lee et al. 1998.)

3 REVIEW OF PREVIOUS LITERATURE

Choudhry (2001) investigated the Month-of-the-Year effect and the January effect with monthly stock returns of Germany, the United Kingdom, and the United States. The sample period was the pre-World War I (WWI) period. For Germany and the UK, the sample period meant time between January 1870 and December 1913, and with the US between January 1871 and December 1913. At the time Choudhry's study was unique in the field of stock market anomalies, due to the usage of a non-linear GARCH model, application of monthly returns data from pre-WWI period, and due to the usage of German and the UK stock returns. Previous studies claimed that by investigating markets during different time periods is the only way to get more proof either for or against anomalies. Choudhry used the pre-WWI period because in these three countries all forms of tax treatment of capital gains or losses in the stock markets were absent. From the National Bureau of Economic Research's (NBER) website the index of stock prices for Germany and the index of Industrial shares for the UK were obtained. The US index was a combination of all industrial and public utilities, and railroad common stocks which was obtained from Historical Statistics of the United States (HSUS). Dividend yields were not included. The results obtained provide evidence of the Month-of-the-Year effect in Germany, the UK, and the US returns, but the January effect was obtained only in the UK and the US returns. Because the pre-WWI period lacks the capital gains or loss tax treatment, Choudhry's results do not provide evidence in favour of the January effect's Tax-Loss-Selling hypothesis nor January effect being a small firm effect. (Choudhry, 2001.)

Moller and Zilca (2008) investigated the evolution of the daily pattern of the January effect across size deciles. The sample included all stocks on the NYSE, the American Stock Exchange (AMEX), and on the Nasdaq Stock Market Exchange (NASDAQ) in the Center for Research in Security Prices (CRSP) monthly data file. The sample period was from 1927 to 2004. While calculating the January effect from monthly returns, the stocks were grouped into 10 deciles based on market capitalization, and for each of the decile continuous equally weighted (EW) and value-weighted (VW) monthly returns were calculated. It was found that there is a positive and higher return in January compared to other months across all but the largest decile. The average January return of the EW portfolio was much higher than of the VW portfolio, although January effect appeared to be strongly related to firm size. After this the statistical significance of the average monthly returns were calculated by using the bootstrapping procedure. The results showed that the average returns in January were statistically significant at the 5% significance level in all but the largest decile. EW portfolio's average return was also significant, whereas VW portfolio's average return was significant only at the 10% significance level. To calculate the daily returns of the January effect, the sample period was divided into two sub-periods, from 1965 to 1994 and from 1995 to 2004. Moller and Zilca (2008) decided to concentrate on the 10 most recent years in the data to examine the possible changes in the January effect. The results showed that in the first sub-period abnormal returns for EW and VW portfolios peaked on day 74, but in the second sub-period abnormal returns peaked already on day 16. The January effect's shorter duration was also consistently found across the 10 size deciles. In the second sub-period January, meaning the first 20 trading days of the year on average, was also divided into two 10-day intervals, days 1–10 and days 11–20. In the first interval of January there were higher abnormal returns and in the second interval there were lower abnormal returns. It was also found that in the second interval of January, there was a substantial decline in trading volume intensity, suggesting that the lower abnormal returns were more likely to be driven by a decline in demand. (Moller & Zilca, 2008.)

Giovanis (2009) studied calendar anomalies of daily stock market exchange indices. The anomalies which the study concentrated on were the Turn-of-the-Month effect, Day-of-the-Week effect, Month-of-the-Year effect, and semi-Month effect. These effects were examined whit 55 different stock market indices, from 51 different countries. Two stock indices were from the UK (FTSE-100 and FTSE-250) and four were from the USA (Dow Jones composite, Nasdaq100, NY composite, and S&P500). The sample period ends to the 31st of October 2008, except with Zambia it ends already on the 31st of December 2007, and the sample period varies with all the stocks. The longest sample period is 58 years, the shortest only 3 years, the median is 11 years, and the average is 14 years. This means that the longest sample period starts in 1950, the shortest in 2005, the median sample period starts in 1997 and in average the sample period starts in 1994. The data was obtained from various websites. Giovanis (2009) used the bootstrap simulated t-statistics and did a seasonality test to study, whether expected returns or volatility had a more certain seasonality. The results showed that three calendar anomalies out of the four studied, were rejected on a global level. The Turn-of-the-Month effect was not rejected, because it was presented in 36 stock indices out of the 55 examined. January effect, which can be concluded as a part of the Month-of-the-Year effect, was also rejected, because it was presented only in 7 stock indices, and in two stock indices the January effect was reverse. Giovanis (2009) found that December, alongside September, had the most frequent seasonality, because 12 stock indices had significantly higher average return compared to other months of the year. In the case of the seasonality in volatility and the Month-of-the-year effect, there is a strong evidence. In December there were significant differences in absolute returns in 27 stock indices, from which 2 were higher average returns and 25 were lower. (Giovanis, 2009.)

Lim, Ng, and Ling (2010) studied the Month-of-the-Year effect on stock returns and volatility with daily data. They used stock market indices of 11 countries in Asia, because previous studies had not been examining calendar anomalies thoroughly on Asian countries. The sample period was from 1990 to 2009. The sample period of 20 years covered the Asian financial crisis in the late nineties as well as the so-called period of stability, which was from January 2000 to March 2005. Lim et al. (2010) used a time-series GARCH approach to analyse the stock return patterns. The main result was that there is a Month-of-the-Year effect in the Asian countries. The results also show that January effect does not exist in the Asian market, but instead December effect is obtained, because it exhibited in the most of the Asian stock markets, except in Hong Kong, Japan, Korea, and China. It is concluded that although Month-of-the-Year effect holds true in different researches while using different periods, it does not follow consistent patterns of having positive January effect. (Lim et al., 2010.)

Sun and Tong (2010) wanted to re-examine the proposition that January effect could be explained by risk. Unlike in the existing literature, Sun and Tong used a time-series GARCH approach instead of the cross-sectional Fama-MacBeth approach. In differentiating, whether risk and or risk premium is higher in January, the time-series approach could give a stronger statistical power. Sun and Tong used the monthly equally weighted return series of the CRSP database. Their sample period covered 80 years of monthly data from 1926 to 2005. The results suggested that market risk is not the factor causing the January effect, instead it is due to the higher price of the risk during the month. The sample period was also divided into two sub-periods from 1926 to 1963 and from 1964 to 2005 to check, whether the results were period specific. Results from both sub-periods reiterated the results from the whole sample period. To determine if risk premium still had explanatory power with size portfolios, Sun and Tong also made a robust check. They used return data on four out of ten smallest-size portfolios from the CRSP database constructed based on the market capitalization of individual stocks. The results from the robust check were qualitatively the same as the previous ones from the study. Sun and Tong's final conclusion was that the January effect is due to higher compensation for risk in January, not due to risk itself. It was still unclear why investors demand higher risk compensation in January. Sun and Tong suggested that the phenomenon could be consistent with the standard consumption capital asset pricing model (CCAPM) if individual investors would have an increasing relative risk aversion (RRA) and would have more liquidity towards the end of the year. Empirical evidence of investors having increased RRA utility function is weak. (Sun & Tong, 2010.)

Agnani and Aray (2011) studied the statistical significance of the January effect on five size-based portfolios' value-weighted returns with US data. The portfolios were constructed at the end of each June by using the June market equity and the NYSE breaking points including dividends. The data was obtained from Ken French's website and the sample period was from January 1940 to December 2006, covering 67 years. Agnani and Aray (2011) used a Markov regime switching model, which allowed them to distinguish high-volatility and low-volatility regimes. The study differed from previous ones, because it considered the January effect and different volatility regimes of stock returns. The estimations for the size-based portfolio returns were controlled for the three risk factors of Fama and French, which also made the model of Agnani and Aray (2011) much richer. The sample period was split into two sub-periods from 1940 to 1983 and from 1984 to 2006, to study whether the financial markets were efficient. The main result was that the January effect existed in all sizes of portfolios. The January effect and the size of the portfolio have a negative correlation, but it fails across the volatility regimes. It was also discovered that for all sizes of portfolios, there is a decline in the January effect during the second sub-period, except for the smallest, where the January effect was even larger. This supports the non-fulfilment of the market efficiency hypothesis. (Agnani & Aray, 2011.)

Marrett and Worthington (2011) wanted to re-examine the Month-of-the-year effect and industry returns in the Australian stock market with daily returns. With market wide, industry and small cap returns, their technical note aimed to provide a more detailed understanding of the effect in all its appearance complimenting previous researches. Marrett and Worthington's (2011) data consisted of twelve different stock indices, each consisting of fifty stocks in business areas within the industry, on the Australian Stock Exchange (ASX). The All Ordinaries index measured the market wide returns, covering around 92 percent of Australian companies by market value, and the Small Ordinaries index measured the return on small capitalization stocks, covering about 7 percent. To measure returns in different industries, ten ASX/S&P industry indices were used. The sample period started om the 9th of September 1996 providing 2,635 end-of-day observations and the data was obtained from Global Financial Data. Marrett and Worthington (2011) used a regression-based approach. The main result is that the Australian stock market has a Month-of-the-Year effect, and the market is not weak-form efficient. At the market level in April, July, and December the returns were up to three times higher than in other months on average. With small cap firms in January, August, and December the returns were 5.3, 3.9, and 4.9 times higher than the mean returns in other months were. Only with small capitalization firms and the telecommunications industry the higher returns could be associated with the January effect. (Marrett & Worthington, 2011.)

Ciccone (2011) examined the January effect from the viewpoint of behavioural framework based on optimistic expectations. According to psychology literature, January is hypothesized to be a month of renewed optimism and that the January effect persist due to the false hope syndrome. In January optimistic investors are expected to dominate in the market, because they bid up the prices of their favoured stocks, making their levels of uncertainty higher. This optimism hypothesis is consistent with the overall stronger market performance and with the findings, that small firms generate superior returns in January. Ciccone (2011) measured information uncertainty by using the Institutional Brokers Estimate System (IBES) unadjusted Summary Files' analyst earnings forecast dispersion. The testing also included portfolio analyses as well as Fama and MacBeth regression equations, which monthly returns data, including dividends, were obtained from the CRSP database. The sample period was from January 1983 to December 2007, covering 25 years and including 651,379 firm-month observations. Stock prices under $5 were removed from the sample to avoid results being driven by bid-ask spreads. In the study of Ciccone (2011) the main result was that the January effect is driven by investor optimism, at least partly. In January, the average monthly return was 1.54% higher than the average of the other months. High dispersion firms outperformed low dispersion firms by an average premium of 1.93%. Although the price of firms with high dispersion run-up in January, their stock returns were relatively low during the rest of the year. These results supported the cycle of renewed optimism in January towards firms with greater information uncertainty, which is consistent with the optimism hypothesis. (Ciccone, 2011.)

Floros and Salvador (2014) examined calendar anomalies of spot and futures returns with daily data. The anomalies which the study concentrated on were the day-of-the-week and the monthly seasonal effects. The sample period was from January 2004 to November 2011, to cover the period before and after the 2008 crisis. The study was restricted to two markets from Europe, FTSE/ASE-20 (Greece) and FTSE-100 (UK), and to two markets from the US, Nasdaq100 and S&P500, and the closing prices were obtained from Datastream. Earlier studies had not yet examined the same calendar anomalies covering the pre-2008 and post-2008 periods with daily spot and futures returns. Floros and Salvador (2014) wanted to study, whether there is support to the calendar anomalies during highly volatile period while using a Markov Regime Switching model. Floros and Salvador's (2014) study's results showed that due to existence of the basis risk the cash markets and futures market's seasonal patterns differed from each other. Calendar effects were also found to be depended on the market situation: they were positive during a low volatility period, but they turned negative during a high volatility period, like a crisis. The study also showed that during low volatile periods for all cash returns there was a positive December effect and for the US spot indices there was a positive January effect. (Floros & Salvador, 2014.)

Li and Gong (2015) investigated the relation between volatility risk and the January effect for the Japanese stock market, applying the methodology of Sun and Tong' (2010) study made five years earlier. The sample consisted of Japanese public firms listed in the Japanese stock market. The sample period was from 1975 to 2008, which was also divided into two sub-periods, from 1975 to 1984 and from 1985 to 2008. This division was done, because anomalies should usually disappear after they are released to the public, and because of the long-term recession in the Japanese economy during the entire 1990s, that resulted of the Plaza Agreement in September 1985, which might have had a significant impact on the Japanese stock market. Li and Gong (2015) used a time-series GARCH approach in their study. The main result of the study was that the January effect exists in the Japanese stock market, and it was greater over the first sub-period, meaning the time before the market anomaly was released to the public. Li and Gong (2015) claimed that investors exploited seasonality during the first sub-period by making abnormal profits bearing less risk. It was found that the Japanese recession might have partially contributed to the decline in the degree of January effect in the Japanese stock market. Although the volatility risk was higher in January, it was not the primary cause for the January effect. It was found that the risk compensation explained the market returns in January over the second sub-period, but neither could it explain the January effect for the Japanese stock market. (Li & Gong, 2015.)

Giovanis (2016) examined the Month-of-the-Year effect, especially the January effect, to recognize monthly patterns without restriction to a regional or national level or to major stock markets. The data and the starting dates of the sample periods were the same as in Giovanis study in 2009. The only difference in the sample periods, compared to the previous study, was that within all the 55 different stock market indices the sample period ended on the 31st of December 2008, not on the 31st of October. Giovanis (2016) used symmetric and asymmetric GARCH models. The main result was that the evidence did not support existence of persistent anomalies, because in each stock market the monthly patterns are formed separately to exploit the profits, which is violating the market efficiency hypothesis. The results show that on the global level January effect does not exist, because it was presented only in seven stock markets. Instead, the highest significant returns were presented in twenty stock markets in December, which can be called as a December effect. (Giovanis, 2016.)

TABLE 1 Summary of the literature review

Research, publication date, and research question	Data and methodology	Main results
Choudhry (2001) Does Month-of-the-Year effect and January effect occur during periods lacking tax treatments of capital gains / losses?	- Monthly data from Germany, UK, and US. - Pre WWI period, covering years 1870–1913. - GARCH approach.	- Month-of-the-Year effect occurred in Germany, UK, and US. - January effect occurred only in UK and US.
Moller & Zilca (2008) How has the January effect evolved after it was first detected?	- Daily and monthly data from NYSE, AMEX, and NASDAQ. - 1927–2004. - Daily and monthly return analysis.	- January effect appeared to be strongly related to firm size, and its duration had become shorter. - Trading volume intensity declined substantially, suggesting lower abnormal returns were due to a decline in demand.
Giovanis (2009) Has expected returns or volatility more certain seasonality?	- Daily data from 51 countries. - The length of sample period varies between 3–58 years, all ending in 2008. - Bootstrap simulated t-statistics and seasonality test.	- Turn-of-the-Year effect occurred in 36 stock indices out of the 55 studied. - December effect occurred. - January effect did not occur.
Lim, Ng, & Ling (2010) Does Month-of-the-Year effect occur in Asia?	- Daily data from 11 Asian countries. - 1990–2009. - GARCH approach.	- Month-of-the-Year effect occurred in Asian countries. - January effect did not occur. - December effect occurred.
Sun & Tong (2010) Does risk explain the January effect?	- Monthly data from the US. - 1926–2005. - GARCH approach.	- January effect was due to higher risk compensation in January, not due to risk itself.
Agnani & Aray (2011) Is January effect conditional to market situation?	- Monthly data from the US. - 1940–2006. - Markov regime switching model.	- Time varying January effect in both volatility regimes. - January effect occurred in all sizes of portfolios
Marrett & Worthington (2011) Does Month-of-the-Year effect occur in Australia?	- Daily data from 12 different indices from ASX. - 1996–2006. - Regression-based approach.	- Month-of-the-Year effect occurred in Australia. - December effect occurred at the market level. - January effect occurred in small capitalization companies.
Ciccone (2011) Can January effect be explained by optimistic expectations?	- Monthly data from the US. - 1983–2007. - Portfolio analysis and Fama & MacBeth regression equations.	- January effect was driven by renewed investor optimism in January towards firms with greater information uncertainty.
Floros & Salvador (2014) Does anomalies occur in spot and futures markets?	- Daily data from FTSE/ASE-20, FTSE-100, Nasdaq100, and S&P500. - 1940–2006. - Markov regime switching model.	- Seasonalities in spot markets were different than in futures markets. - January effect was positive during low volatility and declined when volatility grew.
Li & Gong (2015) Are Sun & Tong's (2010) findings applicable in Japanese stock market?	- Monthly data from Japan. - 1975–2008. - GARCH approach.	- January effect occurred in Japan, and it was greater during 1975–1984. - During 1985–2008 January effect was due to higher risk compensation.
Giovanis (2016) Is there monthly patterns on a global level?	- Daily data from 51 different countries. - The length of sample period varies between 3–58 years, all ending in 2008. - GARCH approach.	- December effect occurred on a global level. - January effect did not occur on a global level.

4 DATA AND METHODOLOGY

4.1 Data

The data of this research adapts the Sun and Tong's (2010) research's data with a few differences. The data is obtained from the Kenneth R. French website, to where the observations have been gathered from the CRSP database. The data consists of monthly equally weighted return series of companies listed on the three major US stock exchanges, the NYSE, the AMEX, and the NASDAQ, for which monthly observations were available. The CRSP database also provides return data on 10 size portfolios, which are constructed based on the market capitalization of individual stocks. Sun and Tong (2010) focused on the four smallest-size portfolios, but in this research all the 10 size portfolios are studied.

In the Sun and Tong's (2010) research the sample period was from 1926 to 2005. The sample period of this research is from July 1926 to March 2021 covering observations from 95 years. The total number of observations used is thus 1137. Sun and Tong (2010) divided their sample period into two sub-periods from 1926 to 1963 and from 1964 to 2005, to find out whether the results were period specific. Such division into sub-periods was not done in this research, because Sun and Tong (2010) found that January effect existed in both sub-periods and neither the magnitude nor the significance did not seem to change.

In addition to the return data on 10 size portfolios, the data includes observations of the Fama and French's three risk factors. The usage of the Fama and French factors as control variables allows the elimination of the returns, which are due to the general risk in the financial markets and thus having an impact on all portfolios simultaneously. (Agnani & Aray, 2011.) The three risk factors are the market factor, the company size factor, and the company's book-to-market value factor. The first factor is familiar from the CAP-model and is defined as additional returns to the general market portfolio. The second factor is used to consider the effect of company size on income variability. This company size factor is determined by subtracting the portfolio returns of big market value companies from the portfolio returns of small market value companies. This factor is often referred by its abbreviation SMB, which comes from words small minus big. The purpose of the third factor is to consider the expected returns in defining the book-to-market value of companies. This factor is determined by subtracting the portfolio returns of low book-to-market value companies from the portfolio returns of high book-to-market value companies. The factor is often referred as HML, which is an abbreviation of high minus low. (Fama & French, 1993.)

In addition to dummy variables for December (Dec) and January (JAN), also COVID-19 dummy variables for March 2020 (MAR20) and April 2020 (APR20), as well as a dummy variable for World War II (WWII), were formed.

4.2 Methodology

Sun and Tong (2010) used the basic GARCH (1, 1) model with a January dummy. In addition to the January dummy, also December, March2020, April2020, and WWII dummies are used in this research. The GJR-GARCH (1, 1) model is specified as follows:

(1.0) $R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 DEC_t + \alpha_3 JAN_t + \alpha_4 MAR20_t + \alpha_5 APR20_t + \alpha_6 WWII_t + \varepsilon_t, \qquad \varepsilon_t \mid \Phi_{t-1} \sim N(0,h_t)$
$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 DEC_t + \beta_3 JAN_t + \beta_4 MAR20_t + \beta_5 APR20_t + \beta_6 WWII_t + \beta_7 \varepsilon^2_{t-1} + \gamma I() \varepsilon^2_{t-1}$

(1.1) $R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 DEC_t + \alpha_3 JAN_t + \alpha_4 MAR20_t + \alpha_5 APR20_t + \alpha_6 WWII_t + \varepsilon_t, \qquad \varepsilon_t \mid \Phi_{t-1} \sim N(0,h_t)$
$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \varepsilon^2_{t-1} + \gamma I() \varepsilon^2_{t-1}$

In Model 1.0 R_t represents monthly returns. JAN is an indicator, and it is one during January and zero during other months. DEC is a dummy variable for December, MAR2020 is a COVID-19 dummy variable for March 2020, APR20 is a COVID-19 dummy variable for April 2020, WWII is a dummy variable for World War II, and I() is in indicator variable having value 1, when ε_t is negative and otherwise zero. The variable h_t is the variance of ε_t conditional upon the information set Φ at time t–1 and is following an ARMA (1, 0) process. In the mean equation the coefficient α_3, i.e., the dummy variable for January, will be positive and significant if there is a January effect in the return series. In the variance equation the coefficient β_3, i.e., the January dummy, will be positive and significant if the volatility risk is higher in January, meaning there might be a January seasonality. It is used as a proxy for the market risk anticipated by investors. (Sun & Tong, 2010.) In Model 1.1 the dummy variables are only in the mean equation.

To test whether volatility risk is the explanatory factor behind the January effect, the following GARCH-M (1, 1) model is used:

(2.0) $R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 DEC + \alpha_3 JAN_t + \alpha_4 MAR20_t + \alpha_5 APR20_t + \alpha_6 WWII_t + \alpha_7 h_t + \varepsilon_t$
$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 DEC_t + \beta_3 JAN_t + \beta_4 MAR20_t + \beta_5 APR20_t + \beta_6 WWII_t + \beta_7 \varepsilon^2_{t-1} + +\gamma I() \varepsilon^2_{t-1}$

(2.1) $R_t = \alpha_0 + \alpha_1 R_{t-1} + \alpha_2 DEC + \alpha_3 JAN_t + \alpha_4 MAR20_t + \alpha_5 APR20_t + \alpha_6 WWII_t + \alpha_7 h_t + \varepsilon_t$
$h_t = \beta_0 + \beta_1 h_{t-1} + \beta_2 \varepsilon^2_{t-1} + \gamma I() \varepsilon^2_{t-1}$

In Model 2.0 if volatility risk during January is the explanatory factor behind the January effect, α_7 will be positive and significant and α_3 will become statistically insignificant or, at least, its magnitude will decline compared to the results from Model 1.0. (Sun & Tong, 2010). In Model 2.1 the dummy variables are only in the mean equation.

5 RESULTS AND ANALYSIS

5.1 Results

The examination of the data was started with multiple linear regression analysis:

(3.0) $$r_{it} = \alpha + \beta_1 DEC + \beta_2 JAN + \beta_3 MAR20 + \beta_4 APR20 + \beta_5 WWII + \varepsilon_{it}$$

(3.1) $$r_{it} = \alpha + \beta_{i-1} + \beta_1 DEC + \beta_2 JAN + \beta_3 MAR20 + \beta_4 APR20 + \beta_5 WWII + \varepsilon_{it}$$

In Model 3.0 r_{it} is the return of the portfolio at time t (i = portfolios 1–10), α is the intercept, β_i is the slope (i = 1–5), and ε_{it} is the error term. In Model 3.1 β_{i-1} refers to lag 1.

In this regression analysis the returns of each of the ten portfolios are explained by the December, January, March 2020, April 2020, and World War II dummy variables, and the analysis is performed throughout the whole sample period. The parameters of the regression model are estimated by the least squares method, which is commonly used while studying calendar anomalies. One lag was exploited in the analysis and Newey-West t-test statistics that were heteroskedasticity robust were included into the analysis. Linear regression analysis was used to observe the occurrence of the phenomenon as well as its link to company size. Next the results and diagnostics of the analyses performed for the entire sample period is gone through. The results are collected into Table 2, which shows coefficients of the variables and their significance.

The results of Model 3.0 in Table 2 show that none of the December dummy variables are statistically significant. All coefficients of the portfolios are positive except in Portfolio 1. When comparing the results between Model 3.0 and Model 3.1 there are not any notable differences with the coefficients of December dummy variables. Instead, the coefficients of January dummy variables are all positive and they are statistically significant at the 1% level in portfolios 1–5 and at the 5% level in portfolios 6 and 7. The January dummy variable coefficients in portfolios 8, 9, and 10 are not statistically significant. This indicates that as the portfolio size increases the significance of the coefficients for January dummy variables decreases, which concludes that the significantly higher January returns occur only in the shares of the companies having the smallest market value. When comparing the results from Model 3.0 and Model 3.1 there are only two differences. In portfolio 5 the significance level decreases from 1% level to 5% level and in portfolio 7 from 5% level to 10% level, meaning the coefficients in these two portfolios get less significant.

Table 2 also shows that with Model 3.0 all March 2020 COVID-19 variables are statistically significant, in portfolios 2–9 at the 1% level and in portfolios 1 and 10 at the 5% level. All these coefficients get negative values ranging from -

25.31 to -11.58, the trend being that the bigger the portfolio size gets the closer to zero the coefficients turn. The MAR20 coefficients with both models 3.0 and 3.1 are equally significant. The coefficients of the April 2020 COVID-19 variables are all positive, but they are less significant. Coefficients of portfolios 4–10 are significant at the 5% level, coefficients of portfolios 2 and 3 at the 10% level and the coefficient of the smallest portfolios is not significant at all. When comparing the APR20 coefficients of the Model 3.0 with the coefficients of the Model 3.1 there are major differences. In all portfolios, except in portfolio 6, the coefficients of the Model 3.1 are more significant than the coefficients of the Model 3.0. In portfolios 4, 5, 7, 8, 9, and 10 the significance level is 1% with the Model 3.1 and 5% with the Model 3.0. The smallest size portfolios dummy variable is not significant with the Model 3.0, but with Model 3.1 it is significant at the 5% level. In the portfolio 2 the significance level increases from 10% to 5% and in portfolio 3 from 10% to 1% when moving from the Model 3.0 to the Model 3.1.

With the Model 3.0 the coefficients of the World War II dummy variables are significant only in portfolios 2 and 3 and only at 10% level. When comparing the WWII coefficients of the Model 3.0 with the Model 3.1 only the smallest size portfolio is statistically significant at the 5% level.

TABLE 2 Linear regression analysis

Port. size	**Smallest size**		**2nd smallest size**		**3rd smallest size**	
Model	**3.0**	**3.1**	**3.0**	**3.1**	**3.0**	**3.1**
(Intercept)	0.4605	0.23490	0.5455 *	0.38393	0.5787 **	0.41282
ar1		0.20396 ***		0.18268 ***		0.20139 ***
December	-0.4492	-0.38806	0.2326	0.11860	0.7270	0.56671
January	6.4073 ***	6.62723 ***	3.9569 ***	3.97320 ***	3.0866 ***	2.98618 ***
March 2020	-22.8105 **	-21.26123 **	-24.4055 ***	-22.98164 ***	-25.3087 ***	-23.30616 ***
April 2020	14.9395	19.72351 **	16.7045 *	21.22471 **	15.4113 *	20.55750 ***
World War II	3.0110	2.45064 **	2.0232 *	1.70368	1.7042 *	1.41460

Port. size	**4th smallest size**		**5th smallest size**		**6th smallest size**	
Model	**3.0**	**3.1**	**3.0**	**3.1**	**3.0**	**3.1**
(Intercept)	0.5900 **	0.44823 *	0.6114 ***	0.49755 **	0.6205 ***	0.50597 **
ar1		0.18075 ***		0.15550 ***		0.15851 ***
December	0.9045	0.75784	0.8119	0.64575	1.1225	0.95766
January	2.4775 ***	2.34618 ***	1.9855 ***	1.87584 **	1.6936 **	1.52956 **
March 2020	-23.1100 ***	-21.17883***	-22.1214 ***	-20.81329 ***	-20.9805 ***	-19.42036 ***
April 2020	14.8100 **	19.02219 ***	15.2586 **	18.71733 ***	13.5895 **	16.93131 **
World War II	1.4397	1.22621	1.1528	1.00769	1.1442	0.99811

Port. size	**7th smallest size**		**8th smallest size**	
Model	**3.0**	**3.1**	**3.0**	**3.1**
(Intercept)	0.5997 ***	0.5079 **	0.6377 ***	0.55637 ***
ar1		0.1365 ***		0.12506 ***
December	1.0156	0.8720	0.8861	0.73847
January	1.3608 **	1.2297 *	0.9254	0.81462
March2020	-22.1197 ***	-20.8469 ***	-18.9877 ***	-17.80080 ***
April2020	16.2703 **	19.3002 ***	13.6023 **	15.97856 ***
World War II	0.9612	0.8664	0.6088	0.55747

Port. size	**9th smallest size**		**10th smallest size**	
Model	**3.0**	**3.1**	**3.0**	**3.1**
(Intercept)	0.5558 ***	0.48666 **	0.5483 ***	0.50638 ***
ar1		0.11035 ***		0.07535 **
December	0.9314	0.84417	0.6837	0.62486
January	0.9557	0.85931	0.1734	0.12178
March2020	-16.9558 ***	-16.03810 ***	-11.4783 **	-10.82380 **
April2020	13.3742 **	15.25301 ***	12.4617 **	13.32717 ***
World War II	0.6485	0.60045	0.2674	0.25922

* Indicates statistical significance at the 10% level.
** Indicates statistical significance at the 5% level.
*** Indicates statistical significance at the 1% level.

Table 3 shows results with the GJR-GARCH (1, 1) model that is exhibited in this research in section 4.2 Methodology. The GJR-GARCH model is divided into two different models, Model 1.0 and Model 1.1. Table 3 shows result only from Model 1.1, where the dummy variables are only in the mean equation and not also in the GARCH equation. Results from Model 1.0 are not shown in this research, because the coefficients of the dummy variables in the GARCH equation were not statistically significant.

The results from Model 1.1 in Table 3 show that the mean monthly return in December is higher in every portfolio than the average monthly return. The biggest difference between the mean monthly return and the average monthly return is in the portfolio 4 and the smallest difference is in the portfolio 8. All the coefficients are statistically significant except for the smallest size portfolio. The coefficients of December dummy variables in portfolios 2, 3, and 8 are statistically significant at the 10% level, and coefficients in portfolios 4, 5, 6, 7, 9, and 10 are statistically significant at the 5% level.

The mean monthly return in January is higher in portfolios 1–7 than the average monthly return. The biggest difference between the mean monthly return and the average monthly return is in the smallest size portfolio and the smallest is in the portfolio 9. The mean monthly returns in portfolios 8, 9, and 10 are smaller than the average monthly return, and the coefficient in portfolio 10 is negative. Also, the coefficients in portfolios 1–7 are statistically significant, at 1% level in portfolios 1, 2, 3, and 4, at 5% level in portfolio 5 and 6 and at 10% level in portfolio 7.

The Table 3 shows that the coefficients of the March 2020 COVID-19 variables are the only ones receiving negative values. The biggest difference between the mean monthly return and the average MAR20 return is in the portfolio 3, the second biggest in portfolio 2 and the third biggest in the smallest size portfolio. The smallest difference is in the portfolio 10. All the coefficients are statistically significant except in the portfolio 1 and in portfolio 9. In portfolios 2, 5, 6, and 7 the coefficients are statistically significant at the 1% level, in portfolios 3, 4, and 10 at the 5% level, and in portfolio 8 at 10% level.

Unlike the March 2020 COVID-19 variables the April 2020 COVID-19 variables are all positive. In portfolio 2 the average April 2020 return has the biggest difference compared to the mean monthly return, and in portfolio 10 the difference is the smallest. All the coefficients are statistically significant except in portfolio 1. The coefficients in portfolios 5, 7, 8, 9, and 10 are statistically significant at the 5% level and the coefficients in portfolios 2, 3, 4, and 6 at the 10% level.

Table 3 shows that with model 1.1 the mean monthly return during World War II is higher in portfolios 1–7 and in portfolio 9 than the average monthly return. The biggest difference between the mean monthly return and the average monthly return is in the portfolio 1 and the smallest is in portfolios 8 and 9. The mean monthly returns in portfolios 8 and 10 are smaller than the average monthly return, and the coefficient in these two portfolios receive negative values. The coefficient of WWII dummy variable in portfolio 1 is statistically significant at the 5% level and in portfolios 2, 3, and 4 they are statistically significant at the 10% level. In the rest of the portfolios, i.e., in portfolios 5–10, the coefficients are not statistically significant at all.

Table 3 shows, that all values of β_0 and β_1 are statistically significant at the 1% level. Also, all values of γ are statistically significant at the 1% level except in portfolio 1, where the value of γ is significant at 5% level. Values of β_7 vary from being statistically significant at 1% level to being statistically insignificant. In portfolios 1, 2, and 10 β_7 is significant at 1% level, in portfolios 3, 4, and 7 at 5% and in portfolios 8 and 9 at 10% level. In portfolios 5 and 6 the values of α are not statistically significant at all.

TABLE 3 Parameter estimates with GJR-GARCH (1, 1) model

Port. size	Smallest size	2nd smallest	3rd smallest	4th smallest	5th smallest
Model	**1.1**	**1.1**	**1.1**	**1.1**	**1.1**
Constant	0.276321	0.363816	0.474284 **	0.460188 **	0.519085 ***
ar1	0.229890 ***	0.162300 ***	0.160583 ***	0.150093 ***	0.141738 ***
December	0.763335	1.056605 *	1.142328 *	1.418651 **	1.154505 **
January	4.374253 ***	2.981784 ***	2.253790 ***	1.601728 ***	1.320707 **
March 2020	-21.660165	-23.258501 ***	-23.589126 **	-21.449575 **	-21.056295 ***
April 2020	13.592872	15.818524 *	14.898676 *	14.091036 *	14.305987 **
World War II	4.672035 **	2.129854 *	1.701408 *	1.488591 *	1.060925
β_0	0.737687 ***	0.942436 ***	1.233179 ***	1.219505 ***	1.520876 ***
β_7	0.071265 ***	0.049616 ***	0.040281 **	0.040848 **	0.032652
β	0.893171 ***	0.885908 ***	0.866798 ***	0.858255 ***	0.839469 ***
γ	0.069128 **	0.109434 ***	0.144964 ***	0.157580 ***	0.189450 ***

Port. size	6th smallest	7th smallest	8th smallest	9th smallest	10th smallest
Model	**1.1**	**1.1**	**1.1**	**1.1**	**1.1**
Constant	0.58466 ***	0.593616 ***	0.624969 ***	0.588339 ***	0.599153 ***
ar1	0.14448 ***	0.122936 ***	0.089303 ***	0.074874 **	0.016854
December	1.17036 **	1.184688 **	0.954093 *	1.009531 **	1.045635 **
January	1.01769 **	0.878595 *	0.589250	0.567214	-0.074199
March 2020	-19.64728 ***	-21.028366 ***	-17.967672 *	-16.195608	-11.381696 **
April 2020	12.62034 *	15.394033 **	12.948693 **	12.777127 **	12.359898 **
World War II	0.96928	0.939078	0.586314	0.627041	0.175084
β_0	1.38749 ***	1.140406 ***	1.129336 ***	0.948131 ***	0.755646 ***
β_7	0.03080	0.046551 **	0.036190 *	0.036149 *	0.078814 ***
β	0.83283 ***	0.841858 ***	0.843623 ***	0.838991 ***	0.843083 ***
γ	0.20867 ***	0.167809 ***	0.174400 ***	0.184167 ***	0.093928 ***

* Indicates statistical significance at the 10% level.
** Indicates statistical significance at the 5% level.
*** Indicates statistical significance at the 1% level.

Table 4 shows results with the GARCH-M (1, 1) model that is also exhibited in this research in section 4.2 Methodology. The GARCH-M model is divided into two different models, Model 2.0 and Model 2.1. Table 4 shows result only from Model 2.1, where the dummy variables are only in the mean equation and not also in the GARCH equation. Results from Model 2.0 are not shown in this research, because the coefficients of the dummy variables in the GARCH equation were not statistically significant.

The results from Model 2.1 in Table 4 are very similar to the result from Model 1.1 in Table 3. The mean monthly return in December is higher in every portfolio than the average monthly return. The biggest difference between the mean monthly return and the average monthly return is in the portfolio 4 and almost as big difference is in the portfolio 1. The smallest difference is in the portfolio 10. All the coefficients are statistically significant except for the portfolio 1. The coefficients of December dummy variables in portfolios 4, 5, 6, 7, 9, and 10 are statistically significant at the 5% level, and coefficients in portfolios 2, 3, and 8 are statistically significant at the 10% level, just like with Model 1.1.

With Model 2.1 the mean monthly return in January is higher in portfolios 1–9 than the average monthly return. Only in portfolio 10 the mean monthly return in January is lower than the average monthly return. The biggest difference between the mean monthly return and the average monthly return is in portfolio 1 and the smallest difference is in portfolio 9, which is consistent with the results in Table 3. All coefficients receive positive values except in portfolio 10. The coefficients in portfolios 1–7 are statistically significant, at 1% level in portfolios 1, 2, 3, and 4, at 5% level in portfolio 5 and 6, and at 10% level in portfolio 7 just like with Model 1.1.

Just like in Table 3, also in Table 4 the coefficients of the March 2020 COVID-19 variables are the only dummy variables receiving negative values. The biggest difference between the mean monthly return and the average MAR20 return is in the portfolio 3, and the smallest difference is in the portfolio 10, which is consistent with the results in Table 3. Compared to the results with Model 1.1, with Model 2.1 only 7 coefficients are statistically significant. In portfolios 1, 4, 5, and 6 the coefficients are statistically significant at the 1% level, in portfolios 7 and 10 at the 5% level, and in portfolio 3 at 10% level.

All April 2020 COVID-19 variables receive positive values with Model 2.1, which can be seen in Table 4. Just like with Model 1.1, in portfolio 2 the average April 2020 return has the biggest difference compared to the mean monthly return, and in portfolio 10 the difference is the smallest. Also, all the coefficients are statistically significant except in portfolio 1. The coefficients in portfolios 7, 8, 9, and 10 are statistically significant at the 5% level and the coefficients in portfolios 2, 3, 4, 5, and 6 at the 10% level. These before mentioned results from Table 4 are almost the exact same as the results presented in Table 3.

Table 4 shows that with model 2.1 the mean monthly return during World War II is higher in all portfolios, except in portfolio 10, than the average monthly return. The biggest difference between the mean monthly return and the average monthly return is in portfolio 1 and the difference diminishes when the portfolio size gets bigger, meaning that the smallest difference is in portfolio 10. The mean monthly returns in portfolios 10 is smaller than the average monthly return. All WWII coefficient in Table 4 receive positive values. Unlike with Model 1.1 none of the coefficients are statistically significant with Model 2.2.

Table 4 shows, that all values of β_0, β_7, and γ are statistically significant at the 1% level. Again, values of α vary from being statistically significant at 1% level to being statistically insignificant. In portfolios 10 α is significant at 1% level, in portfolios 1 and 2 at 5%, and in portfolios 3, 4, and 7 at 10% level. In portfolios 5, 6, 7, and 8 the values of α are not statistically significant at all.

The results in Table 4 also show a trend that the significance level of the GARCH-in-Mean coefficients decreases when the portfolio size increases. In the smallest size portfolio, i.e., in portfolio 1, the coefficient is significant at 1% level. In portfolios 2, 3, and 4 the coefficients are statistically significant at 5% level, and in portfolios 5, 6, 7, and 8 at 10% level. In portfolios 9 and 10 the coefficients are not statistically significant at all.

TABLE 4 Parameter estimates with GARCH-M (1, 1) model

Port. size	Smallest size	2nd smallest	3rd smallest	4th smallest	5th smallest
Model	**2.1**	**2.1**	**2.1**	**2.1**	**2.1**
Constant	-1.438444 **	-1.154289 *	-0.984535	-0.924948	-0.826605
ar1	0.226781 ***	0.167525 ***	0.170541 ***	0.162660 ***	0.158653 ***
archm	0.307665 ***	0.275259 **	0.274545 **	0.274203 **	0.272966 *
December	0.811551	1.033369 *	1.082134 *	1.343228 **	1.071640 **
January	4.306710 ***	2.971860 ***	2.241044 ***	1.567851 ***	1.287297 **
March 2020	-21.014702 ***	-23.042339	-23.906811 *	-22.006779 ***	-21.405698 ***
April 2020	12.964998	15.693461 *	14.616132 *	13.687113 *	13.794885 *
World War II	2.186600	1.437612	1.385250	1.221267	0.871082
β_0	0.820691 ***	1.229345 ***	1.584239 ***	1.602533 ***	1.963514 ***
β_7	0.060049 **	0.048228 **	0.036968 *	0.036789 *	0.028173
β	0.893176 ***	0.876242 ***	0.855520 ***	0.843508 ***	0.822011 ***
γ	0.082721 ***	0.110721 ***	0.146887 ***	0.164048 ***	0.195737 ***

Port. size	6th smallest	7th smallest	8th smallest	9th smallest	10th smallest
Model	**2.1**	**2.1**	**2.1**	**2.1**	**2.1**
Constant	-0.504251	-0.245762	-0.253750	0.046578	0.475869
ar1	0.158139 ***	0.133148 ***	0.100858 ***	0.082165 **	0.017626
archm	0.232474 *	0.185784 *	0.200255 *	0.135266	0.032498
December	1.115122 **	1.128858 **	0.895285 *	0.976295 **	1.042643 **
January	1.014323 **	0.859749 *	0.569195	0.558780	-0.073598
March 2020	-20.096511 ***	-21.194168 **	-18.040612	-16.189691	-11.402562 **
April 2020	12.102020 *	15.064623 **	12.689299 **	12.673061 **	12.339950 **
World War II	0.836588	0.781952	0.492527	0.544521	0.173183
β_0	1.735361 ***	1.353281 ***	1.384944 ***	1.091043 ***	0.766622 ***
β_7	0.026579	0.043734 *	0.032801	0.036854	0.079643 ***
β	0.818706 ***	0.832150 ***	0.830890 ***	0.829231 ***	0.842229 ***
γ	0.211417 ***	0.171044 ***	0.179645 ***	0.184359 ***	0.092235 ***

* Indicates statistical significance at the 10% level.
** Indicates statistical significance at the 5% level.
*** Indicates statistical significance at the 1% level.

5.2 Analysis

This research adapts the Sun and Tong's (2010) research's data and methodology. First the models were estimated in a way where the dummy variables were in both GARCH equations in both models. Unlike in other researches (Sun & Tong, 2010; Li & Gong, 2015) the dummy variables were not statistically significant and were therefore removed from the models. According to the Information hypothesis volatility should be higher than normally during the turn of the year. The results of this research are against this hypothesis.

There are three main results in this study. The first main result is that the monthly series exhibit a December effect that increases when the market value of the companies increases. Choudhry (2001) observed December effect in the German stock market, but not in the UK nor in the US markets, and because value-weighted returns were applied, the obtained results failed to provide support whether it was a small or big firm effect. Choudhry (2001) did not suggest, why the December effect occurred at all, or why in the German stock market. Lim et al. (2010) resulted that most Asian stock markets exhibited December effect. Marrett and Worthington (2011) observed significant December effect in the Australian stock market, that was market wide but also a small firm effect. It is good to point out that in Australia the tax year ends in June, and not in December.

From the results above it can be concluded that this research gives new information about the December effect in the US stock market. The first conclusion is that there is December effect and the second is that it increases as the market value of the companies increases. The possible explanatory factor behind these results is that during December several companies announce new products that they are going launch during the first quarter of the coming year. These announcements increase the prices of the stocks due to increased expectations towards the sales of the companies.

The second main result is that the monthly series exhibit a strong January effect that increases when the market value of the companies decreases. Choudhry (2001) provided significant evidence of the January effect in the UK and the US stock markets, but the results might not be attributed as a small firm effect, due to the usage of value-weighted returns. Moller and Zilca (2008) concluded that January effect still occurred in the US markets, and it was more significant in small market value companies, but its duration was shorter. Lim et al. (2010) found that some Asian countries exhibited January effect that was gradually vanishing. In Sun and Tong's (2010) research, which data and methodology this research adapts, discovered strong January effect on the US stock market. Although they used data on 10 different size portfolios based on the market value of the companies, they concentrated only on the four smallest ones. Despite this, they still noticed that the magnitude and statistical significance diminished as the portfolio size increased. In contrast with most of the previous literature Agnani and Aray (2011) found that January effect existed for all sizes of portfolios in the US stock market, but the effect had slightly declined. Only in the smallest size portfolio the January effect had become even more larger. Marrett and Worthington (2011) observed that in the Australian stock market the January effect related to stocks of small market value companies. Li and Gong (2015) provided evidence that January effect existed in the Japanese stock market for both small and large firms, but the volatility risk in January is higher for small firms than large firms.

The third main result is that in the shares of companies having the smallest market value a GARCH-in-Mean effect is observed. The second and the third main results are in line with some of the previous researches. In this research strong January effect and GARCH-in-Mean effects were observed in the US stock market and their significance decreased, or even disappeared, as the market value of the companies increased. This indicates that volatility is the possible explanatory factor behind the January effect. The results are inconsistent with the ones of Sun and Tong (2010) although this research adapts its data and methodology. The distinguishing factor between this research and the Sun and Tong's (2010) research is that Sun and Tong estimated the models using dummy variables in both GARCH equations in both models and they received statistically significant values, whereas in this research the dummy variables were not statistically significant and were therefore removed from the models.

Although the purpose of this research was to study the possibility of risk being the explanatory factor behind the December and January effect in the US market, one more result is worth mentioning. The results of this research show that all coefficients of the March 2020 COVID-19 variables received negative values and the April 2020 COVID-19 variables received positive values, and almost all coefficients of the COVID-19 variables were statistically significant. In portfolio 1 with both models, Model 1.1 and Model 2.1, the March 2020 dummy variables had the coefficients of -21.66 and -21.01 and in portfolio 10 the coefficients of -11.38 and -11.40. Instead in portfolio 1 the April 2020 dummy variables had the coefficients of 13.59 and 12.96 and in portfolio 10 of 12.36 and 12.34.

6 CONCLUSIONS

The first findings of the January effect were done almost 80 years ago. After the second findings of the effect 45 years ago, the phenomenon has been of interest to both researchers and investors. January effect has been studies plenty with various methods, and the results have been conflicting. In this master's thesis the January effect is researched through literature review and empirical analysis.

In chapter two a theoretical framework is given to this research. The chapter is divided into 5 subchapters. The first subchapter is about the Efficient Market hypothesis, which states that share prices constantly reflect all available information and investors should not be able to generate abnormal profits. The second subchapter is about the history of the January effect. The three remaining subchapters are about three commonly suggested possible explanatory factors behind the January effect, the Tax-Loss-Selling hypothesis, the Information hypothesis, and the Portfolio Rebalancing hypothesis.

In chapter three a review of previous literature, from years 2001 to 2016, is done. The review is as extensive as it can be, since researches, where higher risk during January is being examined as the explanatory factor behind the January effect, have not been done many yet. The literature can be divided into two different kinds of researches based on the methodology used, ones with Markov regime switching model and other ones with a time-series GARCH approach. Most studies related to the January effect use US data, but just like in this literature review January effect has been observed to occur almost everywhere in the World.

In most researches, January effect has been found to be in shares of the companies having the smallest market value. On the other hand, in some researches, the results have been completely opposite. Despite the different results, evidence that the January effect would occur in shares of all size companies, has remained limited. Researches have suspected that for example the riskiness of small companies could be the reason why the January effect is still observed in returns of small companies. Although in several researches the January effect is still observed, it has been stated that the January effect is diminishing or even disappearing. These results are realistic because occurrence of seasonal patterns in the share prices should not be practicable. When anomalies, such as the January effect, come to the public awareness of investors, the exploitation of them should lead to their disappearance from the market.

The chapter four is the empirical part of this research. Sun and Tong's (2010) research's data and methodology, that are presented in chapter three, were adapted into this research with a few exceptions. The purpose was to study the possibility of risk being the explanatory factor behind the December and January effect in the US market using the multiple linear regression analysis and the GJR-GARCH approach. In addition, the relationship of the January effect to firm size was studied. The sample period of this research was from July 1926 to March

2021. The data consisted of ten portfolios organized by the company size. Dummy variables for December, January, March 2020, April 2020, and World War II were set as explanatory variables in the models.

Chapter 5 is divided into two subchapters, results and analysis. There was found three main results in this research. The first main result was that when the company size increases the December effect increases. The second result was that when the market value of the company decreases the January increases. The third main result was that a GARCH-in-Mean effect was observed in shares of small market value companies.

New studies would be needed where volatility is the explanatory factor behind the January effect with the GARCH approach to confirm the results of this research. In the future studies, the reliability of the models could be improved for example with weekly data instead of monthly data. Also, the December effect detected in this research needs more studies to confirm that opposite to the January effect the December effect is a big firm effect. Although the focus in this study was not in the COVID-19 dummy variables, the research showed interesting results about them that could be examined in the future studies.

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