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School of Business and Management
Strategic Finance and Business Analytics

Master's Thesis

Nested Anomalies in U.S. Stock Market

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Tämän työn tarkoitus on tutkia kalenterianomalioita fundamenttianomalioiden sisällä Yhdysvaltain osakemarkkinoilla. Tutkielmassa käytetyt kalenterianomaliat ovat puolivuotisilmiö ja kuukausianomalia. Tukimusperiodi on vuodesta 1963 vuoteen 2019. Portfoliot, joiden sisällä kausiluontoisia tuottoja tutkitaan, perustuvat yhtiökohtaisiin erityispiirteisiin, joita ovat *yhtiökoko, omapääoma/markkina-arvo, operatiivinen kannattavuus, nettotulos/markkina-arvo, kassavirta/markkina-arvo, osinkotuotto, momentum, siirtovelat, beta-kerroin, netto-osakeannit* ja *osakehinnan varianssi*, joista jokainen erityispiirre kuvaa eri anomaliaa. Tutkimuksessa vertaillaan osta ja pidä - , puolivuotis- ja kuukausistrategiaa jokaisen anomalian sisällä. Portfolioiden suoriutumista arvioidaan tuottojen ja riskikorjattujen tuottojen perusteella. Tulosten perusteella arvoanomalia yhdistettynä puolivuotisanomalian ja tammikuu yhdistettynä yhtiökoko- ja arvoanomalian kanssa ovat tuottaneet muita strategioita paremman lopputuloksen. Tulosten perusteella lähes jokaisen anomalian sisällä esiintyy puolivuotisanomaliaa eikä kohonnut riskitaso puolivuotisanomalian aikana selitä tätä ilmiötä. Tämän lisäksi tammikuu-ilmiö, talouden suhdannevaihtelut ja markkinoiden likviditeetti eivät vaikuta tulosten pätevyyteen. Kausittainen tarkastelu viittaa puolivuotisanomalian olevan pysyvä ilmiö fundamenttianomalioiden sisällä. Tulosten perusteella portfolioiden tuottoihin kohdistuu aikakausittain vaihtelevaa riskipreemioita, joka voi osaltaan selittää kausiluontoisia ylituottoja anomalioiden sisällä.

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ABSTRACT

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This thesis aims to examine strategies trading calendar anomalies within fundamental anomalies in U.S. stock market. Calendar anomalies utilized in this thesis are half-year anomaly and month-of-the-year effect and the time period of investigation is between 1963 and 2019. Portfolios investigated within these seasonals are based on firm-specific fundaments (*company size, BE/ME, operational profitability, E/P, CF/P, D/P, momentum, accruals, beta, net share issuances* and *variance of stock price*) which each mimic a certain fundamental anomaly. Approach in this thesis is to study buy-and-hold strategy, half-year strategy and month-of-the-year strategy within each factor portfolio. Performance of each investing strategy is evaluated in terms of absolute returns and risk-adjusted returns. Results indicate the superiority of value anomaly (*BE/ME, CF/P* and *E/P*) within half-year anomaly and superiority of value and size effect within the month of January. Predominantly all examined fundamental anomalies tend to exhibit strong half-year effect. According to the results of this thesis, comprehensively better portfolio returns during half-year anomaly period are not merely compensation for inflated risk associated with the time period. January, macro-economic conditions and market-wide liquidity changes do not account for this half-year effect. Moreover, periodical investigation suggest somewhat steady trajectory of half-year anomaly returns within fundamental anomalies. Results show that portfolios exhibit time-varying risk premium that can partially account for seasonalities within fundamental anomalies.

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On 22.6.2020 in Helsinki,
Vertti Vuohelainen

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LIST OF ABBREVIOATIONS

SIZE:	Portfolio based on market capitalization of company. Long position on small capitalization stocks. Short position on large capitalization stocks.
BE/ME:	Portfolio based on book-to-market multiple of company. Long position on high BE/ME stocks. Short position on low BE/ME stocks.
OP:	Portfolio based on operating profitability of company. Long position on high OP stocks. Short position on low OP stocks.
E/P:	Portfolio based on earnings-to-price multiple of company. Long position on high E/P stocks. Short position on low E/P stocks.
CF/P:	Portfolio based on cash-flow-to-price multiple of company. Long position on high CF/P stocks. Short position on low CF/P stocks.
D/P:	Portfolio based on dividend-to-price (dividend yield) of company. Long position on high D/P stocks. Short position on low D/P stocks.
MOM:	Portfolio based on company's stocks price movements. Long position on stocks with upward movement in the past. Short position on stocks with downward movement in the past.
ACC:	Portfolio based on level of accounting accruals of company. Long position on stocks with low ACC. Short position on stocks with high ACC.
BETA:	Portfolio based on company beta coefficient. Long position on stocks with low beta. Short position on stocks with high beta.
ISS:	Portfolio based on net share issuances of company. Long position on stocks with low ISS. Short position on stocks with high ISS.
VAR:	Portfolio based on past variance of daily returns. Long position on stocks with low VAR. Short position on stocks with high VAR.

1. INTRODUCTION

Risk and return. These words encapsulate two main components of investing. For a long period of time investors and researchers have tried to come up with different investing strategies that would enable one with systematic risk-adjusted excess returns. In order to achieve this, different risk factors and market anomalies, thus deviations from market efficiency have been utilized. In fact, risk factor investing has become an important concept within investing world and its popularity has grown over the recent years. (Cazalet & Roncalli, 2014). This research aims to describe the dynamic relationship between seasonalities and anomalies and provide a holistic view on nested anomaly strategies based on these principles.

Primary objective of a mutually owned company is to maximize its profits and therefore wealth of its shareholders. Moreover, we can assimilate this objective and expect the same form every rational investor constructing a portfolio: to maximize the expected returns given risk associated with this. Intertemporal choice between asset allocation and future consumption can be seen as incentive to seek the best performing strategy in the stock markets. The modern portfolio theory of Markowitz (1952) declares that investors tend to maximize the expected returns of the portfolio whilst minimize the variance of returns, when making investment decisions. According to this theory, investors want low risk and high reward. In addition to modern portfolio theory, later on the Capital Asset Pricing model (CAPM) by Sharpe (1964), Lintner (1965) and Moss (1966) was introduced to explain the returns of the portfolio or individual stock with respect to its sensitivity to overall market returns. Nevertheless, wide range of researches on different market anomalies have documented the existence of certain portfolio formation factors that have granted an investor with abnormal risk-adjusted returns. Thus, casting a shadow on these traditional theories.

Anomalies are identifiable inefficiencies in stock markets based on for example firm-specific multiples or seasonalities. There are a large scale of different anomalies and a wide range of studies detecting the existence of anomalies and persistency of them. The basic motivation behind any anomaly is the access to risk-adjusted excess returns. Many researches have proven that strategies trading different anomalies have generated larger than market returns.

However, studies have documented that usually anomalies tend to deteriorate or disappear after they are publicized, for they have been exploited by enough large number of individuals. Thus markets correct the mispricing.

Fama and Kenneth French (1992) discovered that the assumed linear cross-sectional relationship between mean excess returns and exposure to the market factor in CAPM was in fact violated in US stock markets. In their research they pointed out, that in fact a major part of cross-sectional dispersion in mean returns was explained by exposure to two other factors, size and value. This led to a formation of a famous three factor model of Fama and French, which uses market risk of CAPM, size and value factor to explain cross-section of mean returns. Their research appointed that small companies and companies with a high book to market multiple tend generate higher risk-adjusted returns in the long run. Their study was amongst first to document value and size anomaly. Another anomaly widely recognized in the stock markets, momentum, was discovered by Jegadeesh and Titman (1993) in their research. They proved that a portfolio, which buys stocks that have performed well in the past and contrariwise sells stock, that have performed poorly, was able to generate significant excess returns.

Stock markets have also been discovered to exhibit seasonal variation in returns, calendar anomalies. Many studies have documented that market returns and even individual stock returns, tend to have a certain time dependency. Thereby a significant part of returns usually occur during a specific time period within the year, for example a certain day of a week, month or longer period. Numerous of studies have noticed average stock returns being higher during the period from November to April each year compared to the average returns of the remainder of the year. Bouman & Jacobsen (2002) studied this Sell in May effect (henceforth also half-year anomaly) with a global perspective. They compared different market returns generated within a traditional buy-and-hold -strategy and half-year anomaly. The results were persuasive. Half-year anomaly was present in every market index they examined. Moreover, the anomaly was quite persistent over time during the period of 1973-1996 in their research. January effect is another widely known calendar anomaly. Rozeff and Kinney (1976) examined monthly returns in U.S. stock markets and noticed that January mean returns were significantly higher compared to other months on a yearly basis. Keloharju, Linnainmaa & Nyberg (2016) examined seasonalities of returns in their research.

They selected stocks based on their historical same-calendar-month returns in the portfolio and noticed that this strategy was able to generate on average return of 13% per year. They concluded, that this seasonality was remarkably pervasive and arose at different frequencies all over the capital markets. Furthermore, they pointed out that the factors generating seasonalities were in fact the same as those generating differences in cross-section of stock returns. Moreover, align with previous researches on firm specific factors, the size factor was the single largest source generating seasonal deviations in individual stock returns.

Numerous of studies have examined different firm-specific factors affecting the mean excess returns and moreover, even combinations of these. However, fewer researches have been conducted about the intrinsic qualities of these different factors, to be more specific, how evenly returns are distributed within these factors. Thus, studies on the possible time-variation of returns within anomalies are scarce, which offers this thesis an academic gap to fill. In addition to this, the substantial effect of market timing on average returns and possibility to accompany these returns with previously investigated anomalous risk factor returns creates a clear motivation to investigate this matter.

1.1. Objective and research questions

This thesis examines investing strategies trading calendar anomalies within fundamental anomalies, in this thesis referred as *nested anomalies*. Much like fundamental anomalies based on some firm specific feature, calendar anomalies have also resulted in abnormally large average returns. Therefore, it is rational to assume, that a combination of these anomalies would result in somewhat significant results. Objective of this research is to come up with a conclusion on whether fundamental anomalies exhibit persistent seasonal variation in their returns. Calendar anomalies examined within fundamental anomalies are half-year anomaly and month-of-the-year effect.

Bouman & Jacobsen (1997) appointed, that it may be possible that the seasonal higher returns during half-year anomaly might be caused by a higher risk during that specific period within a year. Thus, the overall objective is to find out, which firm-specific factors investor should take into consideration when making an investment decision and whether an investor should replace buy-and-hold principle with seasonal holding period on a yearly basis in order to achieve better outcome. Null hypotheses in this thesis, is that markets are efficient and therefore no abnormal returns are available when utilizing nested anomaly strategies.

We can formulate the research questions of this thesis as following:

1. *Are there differences between buy-and-hold anomaly-portfolios and anomaly-portfolios trading seasonalities in terms of absolute returns?*

2. *Are there seasonal deviations in returns within anomalies on a risk-adjusted basis?*

3. *Are there statistically significant calendar anomalies within fundamental anomalies?*

4. *Is half-year effect within fundamental anomalies a time-varying or persistent phenomenon?*

1.2. Methodology

The thesis uses data from U.S. stock market including NYSE, Nasdaq and Amex stocks from 1963 to 2019. Data is obtained from Kenneth French's website[1]. Firm specific fundaments used in this thesis as proxies for anomalies are company *size*, *B/M*, *E/P*, *operating profitability (OP)*, *CF/P*, *D/Y*, *momentum (MOM)*, *accruals (ACC)*, *beta*, *variance (VAR)* and *net issuances (ISS)*. These factors represent different anomalies in this thesis. Portfolios are formed according to these factors and these portfolios then divided into deciles. From each of these portfolios top and bottom deciles are investigated as long and long-short strategies. Seasonalities, that are investigated within beforementioned factors, are half-year anomaly and month-of-the-year effect.

In order to detect possible seasonalities within anomalies, conventional methods are used. These include observing returns of each portfolio and risk of each portfolio with measures of volatility, beta, Sharpe and adjusted Sharpe. Jobson Korkie -test is employed to observe if there is significant difference between each factor portfolios' Sharpe ratio and market portfolios' Sharpe ratio. In addition to these measures, regression models are used for each nested anomaly. The statistical significance of the seasonalities are then observed from the results of the regressions. This thesis also provides a robustness checks for results by examining possible factors affecting the results and regression with conditional variance.

Results of this thesis show significant half-year anomaly and January effect. Value investing combined with half-year anomaly have outperformed other strategies in terms of absolute returns and market portfolio return in terms of risk-adjusted returns. Moreover, examined anomalies tend to systematically exhibit strong half-year effect and therefore superior returns during the period from November to April. The results also indicate a rather ample low volatility anomaly during the period outside half-year anomaly.

1.3. Limitations of the study

Although seasonalities and anomalies have been discovered in wide range of markets, this study focuses solely in U.S. stock market. (e.g., see Keloharju, Linnainmaa & Nyberg, 2016; Bouman & Jacobsen, 1997) Moreover, this thesis examines only a fraction of possible factors explaining the returns from a wide universe of identified risk factors (Cazalet & Roncalli, 2014).

The choice between equally- and value-weighted portfolios is arbitrary. This study focuses on value-weighted portfolios; thus they are widely used in financial research. (e.g., see Fama & French, 1996; Gharghori, Lee & Veeraraghavan, 2009). Even though anomalies have also been discovered in wide range of different asset classes, for example in government bonds, futures, commodities and currencies (e.g., see Asness, Moskowitz & Pedersen, 2013; Kho, 1996; Erb & Harvey 2006; Novy-Marx, 2012), this thesis investigates solely returns of publicly traded U.S. equities. Assumption of zero-cost portfolios is employed throughout this thesis. Especially strategies trading seasonalities within anomalies would face transaction costs, taxes and optional costs related to investing activity, which could alter the results.

1.4. Structure

The structure of this thesis is following. Section 2 is literature review, which goes through previous researches related to anomalies and seasonalities. Section 3 describes the theoretical background behind assumptions and methods employed in this thesis. Section 4 describes in detail the data and methodology. Section 5 includes the empirical results research and the related robustness checks for them. Section 6 concludes the paper.

2. LITERATURE REVIEW

Frankfurter and Mcgoun (2001) define anomaly as “an irregularity, a deviation from the common or natural order, or an exceptional condition.” Neoclassical theories assume, that markets are efficient, thus all available information is fully reflected to stock prices (Fama, 1970). In finance, anomalies are considered as systematic deviations from the efficient market theorem. Malkiel (1999, 132, 142, 145), argues, that fundamental analysis on equities does not work, firstly because the information and analysis may be incorrect, secondly because the security analyst’s estimate of so-called value may be faulty and lastly the market may not correct its mispricing, thus the security price might not converge to its value estimate. He also shoots down technical analysis and claims, that the belief in repetitive pattern in the stock markets is due to statistical illusion. Therefore, with a traditional buy-and-hold strategy, an investor typically makes as much or more money. However, due to a development in econometrics, more inconsistencies have been found in the data and techniques as well as strong evidence against market efficiency, which cannot be ignored. (Jensen, 1978)

2.1. Fundamental anomalies

2.1.1. Value anomaly

Lakonishok, Shleifer and Vishny (1994) describe, that value anomaly is the tendency of stocks with low prices relative to earnings, dividends, book assets or other measures of fundamental value to outperform market returns. Their research points out, that value strategies beat glamour strategies and market return, because market participants seem to consistently overestimate future growth rates of glamour stocks relative to value stocks.

Sharpe (1964), Lintner (1965) and Moss (1966) invented the CAPM model (1) which states that the returns of the asset is dependent on risk free rate (R_f), beta coefficient (β) which describes the asset’s return fluctuations relative to the market fluctuations and market risk premia ($E(R_m) - R_f$) which is the difference of market return and risk free rate of return. Basically, all factor models are somewhat based on CAPM with additional factors explaining the returns. Therefore, even today, CAPM provides valuable insights on asset's expected returns.

$$E(r_i) = R_f + \beta(E(R_m) - R_f) \tag{1}$$

Perhaps one of the most famous duo to investigate size and value factors among stock returns were Fama and French (1992). They derived the so-called Fama-French-three factor model (FF3), which implies that a stock return is dependent on three explanatory variables: market, size and value. FF3 is based on CAPM with additional size and value factors.

$$R_t - R_f = \alpha_i + \beta_1\left(R_m - R_f\right) + \beta_2(SMB) + \beta_3(HML) + \varepsilon_i \tag{2}$$

Fama and French calculated size premia as small company returns minus big company returns (SMB) and value premia as high book-to-market companies minus low book-to-market companies (HML). In their research, market beta, company size, Earnings to Price -ratio (E/P), leverage and book-to-market equity were used to explain the cross section of average stock returns in the U.S. stock markets between 1963–1990. Stocks were divided into ten groups based on their book-to-market multiple and reranking was done annually. The highest book–to–market quintile of stocks notably outperformed the lowest book-to-market quintile. They found out, that the most dominant variables in explaining the cross section of average stock returns were size and book-to-market equity factors, meaning, that a small capitalization companies with high B/M multiples tend to generate more capital gains than other stocks in the long run. On the other hand, Gharghori, Lee and Veeraraghavan (2009) tested the explanatory power of Fama-French-three factor model with a smaller group of portfolios in Australian markets. They discovered, that the three-factor model was inadequate model to explain the returns of the portfolios. They concluded, that the three-factor model may have explanatory power in U.S. stock markets, but not so much in Australian markets.

Fama and French (1993) expanded their previous research from Fama-MacBeth cross-sectional regression to time series regression and added two explanatory bond market factors related to maturity and default risk. They found out, that their five-factor model did also a good job in explaining the common variation in bond and stock returns and the cross-section of average returns. Despite the findings in their research, they emphasize the risk related to these investing strategies and argue that companies, which have a low level of P/B multiple, tend to be a financially distressed companies with high level of leverage, hence an elevated risk of bankruptcy. However, Lakonishok, Shleifer, and Vishny (1994) refuse the higher risk explanation for superior returns in value investing. Their empirical evidence suggested, that value investing was not fundamentally riskier than glamour strategies and according to their results, investing in value stocks between 1968 to 1990 has evidently generated abnormal returns. The authors suggest that possible explanations could be that investors are simply not aware about the existence of value stocks or that authors have engaged in data snooping in the research.

Dennis *et al*. (1995) investigated, whether size and value effect were so pervasive in the U.S. stock markets that they would prevail, even when considering transaction costs and alternative rebalancing periods of one, four and ten years. The results of the research were persuasive. The Fama-French optimal portfolios provided an investor with the highest absolute returns of the 25 portfolios constructed. Another significant finding was that the spread between the returns of optimal (high BE/ME-small size) portfolio and non-optimal (low BE/ME-large size) portfolio was 10.04% for one-year rebalancing periods, 13.54% for four-year rebalancing period and 11.53% for ten-year rebalancing period. The authors concluded that after adjusting the returns with a one percent transaction costs and annual rebalancing, an investor would have beaten the market between 1963–1988 by 4.82% with the high BE/ME and small size portfolio. These empirical findings indicated that different rebalancing periods and cost associated with them were somewhat irrelevant. Thus value investing would be practically beneficial for an investor.

Another research on value investing was conducted by Piotroski (2000). He found out that compared to stand-alone B/M portfolio selection, mean return earned by the investor can increase by 7.5% percentage points annually when selecting financially strong high book-to-market-ratio companies. Moreover, benefits of financial statement analysis among high

B/M firms are concentrated mostly in small and medium size companies with low share turnover and no analyst coverage. Moreover, Piotroski came up with a F-score for value investing, which observes company's profitability, leverage, liquidity, source of funds and operating efficiency by giving points from 0–1 with respect to information in company's financial statement. Eventually the F-score for each company is between 0–9 and it is then used to find the best value stocks. Based on results, companies with high F-score earned mean market adjusted return of 0.134 over the subsequent four quarter whereas companies with low F-score resulted in mean market adjusted return of –0.096. The authors found out that the spread of 0.230 between high F-score and low F-score returns was statistically significant with a confidence level of 99%.

Chen and Zhang (1998) observed the risk associated with investing in value stocks. They came up with a conclusion, that higher returns for value stocks are compensation for higher risk. Their results suggested that strong value effect persist in U.S. stock markets, whereas being less persistent in Japan, Hong Kong, Malaysia and undetectable in Taiwan and Thailand. On a contrary, Chan and Lakonishok's (2004) evidence suggest, that common measures of risk do not support the argument that value premium would be result of a higher riskiness of value stocks. Instead, behavioral factors and the agency costs of delegated investment management could be the main architect of value-growth spread.

Nicholson (1968) was among first to notice, that in addition to other price ratios, there was a significant distinction in returns between low and high price–to–earnings (P/E) portfolios. He reported that price changes from 1937 to 1963 show five-year appreciation averaging 32% for stocks with P/E ratios over 20 and 90% for stocks with P/E of 10 or less. Basu (1977) also formed portfolios according to P/E ratios and pointed out, that stocks with low P/E ratios have outperformed those with high P/E ratios in U.S. stock markets between 1957–1971. He concluded that from the point of view of investors, a "market inefficiency" seems to have existed. In addition to previous researches on P/E multiple, O'Shaughnessy (2005, 76,131) found out that low P/E especially amongst large capitalization stocks resulted in a significant return, since the compounded return of the 50 low-PE large stocks was 2.80% higher than large stocks' average returns. However, he also proved, that Price/sales ratio acted as a better indicator for future risk-adjusted returns.

Kwag and Lee (2006) examined, whether value investing is superior to growth investing in different business cycles. They formed value-oriented portfolios, with a high BE/ME, E/P, CF/P, and D/P whereas growth-oriented portfolios contained stocks from other end of same firm specific multiples. The results were in line with previous researches. Value oriented portfolios outperformed the growth-oriented portfolios. Furthermore, the benefits of value investing, according to empirical evidence, seemed to be even greater during periods of economic contraction than during periods of economic expansion.

High dividend yield is also notified as one of value investing criteria. According to the results of Rozeff (1984), there was significantly positive correlation between dividend yield and expected returns of a stock, thus high dividend yield indicated high expected returns. Explanation to this phenomenon was the connection between stocks dividend yield and risk premium required by investors. Thus, with high expected return of investors the present value of dividends is low and therefore dividend yield should be high.

Fundamental anomalies are not just limited to certain country or continent, rather they appear everywhere, as Asness, Moskowitz and Pedersen (2013) summarized in their research. They concluded, that value and momentum ubiquitously generate abnormal returns in eight different markets and moreover not just among individual equities but also in country equity index futures, government bonds, currencies, and commodity futures. Another significant observation in their research was that in the US, UK, Continental Europe and Japan value and momentum anomaly combined resulted in a better outcome than either one alone.

Cakici, Chan and Topyan (2017) investigated fundamental factors affecting stock returns in Chinese markets from 1994 to 2011. The researchers noticed that size, BE/ME, CF/P and E/P ratio have a substantial predictive power over the stock returns. These results were obtained using Shanghai and Shenzhen Stock Exchanges. Their research also pointed out, that E/P ratio was relatively less powerful predictor of cross section of stock returns than other variables related to value investing, and momentum anomaly itself had no significant prediction power over the returns itself. Contrariwise, results of Novy-Marx (2013) indicated that profitability of firm had roughly the same predictive power over the returns as BE/ME ratio. Novy-Marx concluded that profitable companies tend to generate significantly higher returns compared to unprofitable companies and therefore, they are trading with significantly higher valuation, which excludes them from value strategies. In addition to this, Gezelius (2020) argued that the magnitude of traditional P/B ratio and other value metrics in predicting future returns is diluted because of the rise in intangible assets and therefore, outdated accounting treatments.

According to researches, the reasons for value anomaly are many. Lakonishok, Shleifer, and Vishny (1994) suggested that value stocks to exhibit superior risk-adjusted returns simply because investors are not aware of them, which then leads to mispricing of these stocks. Another possible reason was provided by Fama and French (1992). According to their research, an investor exploiting size and value anomaly is rewarded with better returns in order to compensate the risk they are taking. Therefore, an elevated risk of substantial losses in investing provides investor with significant value premia. Petkova and Zhang (2005) recorded the risk associated with value and growth investing. Their empirical evidence suggested, that time-varying risk goes in the right direction in explaining the value premium. Thus, value betas have a tendency to covary positively with the expected market risk premium. However, the covariation between the value-minus-growth betas and the expected market risk premium was not substantial enough to account for the studied magnitude of the value premium in the context of conditional CAPM. Furthermore, Ball (1992) argued that there are two possible explanations on earnings-to-price anomalies, the first one being that the markets are truly inefficient, which means that mispricing in the markets allows true abnormal returns for investors at zero cost. The second explanation that the markets are efficient, and the measured abnormal returns are just biased estimates of pure economic profits.

In the long run, value stocks have systematically outperformed growth stocks even though growth stocks have higher betas. Thus, they seem to be riskier than value stocks. Zhang (2005) investigated this matter and came up with a contrarian conclusion. His study demonstrates that assets in place are in fact much riskier than growth options, especially in the times of economic contraction and market crashes, when the price of risk is high. This is due to a cost reversibility and high countercyclical price of risk. In other words, during the bad times value companies are burdened with more unproductive capital, hence finding it more difficult to reduce their capital compared to growth companies. In the times of economic expansion, growth companies invest and expand their businesses, whereas value companies find their unproductive capital become productive again. Thus, expanding capital is less urgent to value companies. Since expanding capital is rather easy for growth companies, their dividends and returns do not covary much with the economic movements. This results in a high dispersion on risk between value and growth strategies in bad times and low or even negative dispersion in good times. Thus, the value premium should be equal the risk dispersion between value and growth strategies times the price of risk. This is in line with the study of Fama and French (1995), which suggested that low P/B tend to indicate low level of earnings, whereas high level of P/B indicated strong earnings, and also, with Asness *et al*. (2000), who pointed out that the earnings growth spread of value versus growth strategies is positive indicator of the value-minus-growth return.

A slightly different approach was taken by Leivo and Pätäri (2011). They investigated the value investing when taking into account the price momentum of the stocks. Value portfolios were formed based on several multiples from which a composite value measure was formed. One mentionable detail in their study was the use of EBITDA/EV (Earnings before interest payments, taxes, depreciations and amortizations / Enterprise value) along with other more conventional multiples and composite criteria. Their study was conducted on Finnish stock market between 1993-2008, excluding financial stocks. The results indicated that when combining value investing with price momentum, investor can obtain statistically significant returns with a lower volatility. However, authors appointed that with the inclusion of momentum in the value portfolios, the asymmetry of the return distributions of top-sextile of value portfolios increased into direction, that is undesirable for investor. The conclusion was that according to the adjusted Sharpe ratio, the best performing portfolio during the 15-year investigation period was the composite portfolio formed on D/P, BE/ME and EBITDA/EV, and price momentum.

2.1.2. Size effect

Some studies have shown, that firms with a small capitalization tend to outperform markets in the long run, when considering investors' absolute returns. Banz (1981) was among first to study this size effect. He divided stocks listed on the NYSE into quintiles based on the company's market capitalization and investigated the returns of quintiles from 1926 to 1980.

The results indicated that small capitalization firms have had higher average risk-adjusted returns than large capitalization firms. Moreover, small capitalization firms outperformed all other quintiles and indexes. Banz concluded that size effect provided evidence that the famous Capital Asset Pricing model (CAPM) is, in fact, mis-specified. Reinganum (1983) obtained same kind of results. He displayed that size effect was substantial, even without daily rebalancing of the portfolio and noticed that in general, the smaller a firm in a portfolio, the better it performed. Similar results were documented by Keim (1983), who reported a size premium of 2.5% per month between 1963-1979 and moreover, that abnormal returns were largely due to January effect. Empirical evidence showed that small companies have systematically higher betas, but the difference in betas could not fully explain the difference in returns. By contrast, Lamoureux and Sanger (1989) reported, that small capitalization companies tend to have lower betas than large companies in Nasdaq and the average size premium was 2% in Nasdaq and 1.7% in NYSE and Amex per month in the period of 1973-1985.

However, whether size effect truly results in abnormal returns is debatable. Dreman (1997) clarified, that the results of Banz (1981) were unsatisfactory, since the study included only stocks from NYSE, which are substantially larger than small capitalization stocks from other exchanges. He also stated, that some of the small capitalization stocks are so illiquid, that one could not simply buy them in large quantities. In addition to this, Horowitz, Loughran and Savin (2000) suggested, that previous findings on size effect were not robust. According to their findings, the size effect was somewhat present from 1963 to 1981 but especially in December 1981, after the launch of Dimensional Fund Advisor's 9-10 fund, small firms underperformed large firms by 16 basis points per month. Authors claim that possible reason for underperformance was that investors became aware of the size effect, thus stock prices of small companies adjusted accordingly. Yet another possible explanation is the recent increase in passive indexation, hence more weight is given to large capitalization firms at the expense of smaller firms.

Size effect is widely reasoned with risk associated with smaller companies. One explanation has been the trading costs and illiquidity linked with small capitalization companies. Others argue that so called size effect is nothing more than a statistical fluke. (van Dijk, 2011) Vassalou and Xing's (2004) findings displayed, that size effect was only significant in highest default risk quintile. Therefore, elevated risk of default explained the size premia and size effect should be considered as default effect. In addition to this, Stoll and Whaley (1983) proved that practically it is difficult to earn abnormal risk-adjusted returns with small cap stocks when considering all transaction costs in NYSE between 1960 to 1979. On the other hand, Amihud and Mendelson (1986) explained the size premia with holding period and bid ask spread. Their empirical evidence suggested, that the longer the holding period, the larger the bid-ask spread tend to be with stocks in the portfolio. Furthermore, because the substantial trading costs are diluted over a longer holding period, the larger the spread, the smaller the compensation required for an additional increase in the spread. Thus, this offers possible explanation for abnormal returns from small cap stocks.

2.1.3. Momentum

The tendency of past winner stocks to outperform other stocks and past loser stocks to underperform other stocks is called momentum anomaly. Traditional momentum anomaly is usually associated with Jegadeesh and Titman's research (1993). In their study, stocks were selected to portfolios based on their returns over the past 3, 6, 9 and 12 months with equal holding periods, consisting overall 16 strategies. Remarkably, almost all strategies resulted in significant returns and strategy based on stocks' past 12-month returns with a holding period of 3 month resulted in the best outcomes. In addition to this, the study measures the possible effect of firm size and beta on 6-month/6-month strategy by formulating subsamples based on these fundaments in order to conclude whether the profitability of the strategy is confined to any particular subsample, therefore providing evidence about the source of the profits. The results were insignificant. With respect that only small differences in the magnitude of returns were found, thereby indicating that the profitability of strategy was not confined to any particular subsample of stocks. Another significant finding was that momentum portfolios tend to perform poorly in January, which was due to a underperformance of small cap companies in the portfolio.

Rouwenhorst (1996) obtained somewhat similar results concerning momentum anomaly in the stock markets as previous researches. He discovered that internationally diversified portfolio, which invests in medium-term winner stocks and sells medium term loser stocks earns around 1 percent per month. These results hold across all size classes. According to him, the outperformance lasts about one year and cannot be explained by conventional measures of risk. Another remarkable finding was that when controlling the returns for market risk and size factor, the abnormal performance of the momentum strategies increases. In addition to international evidence of momentum anomaly, Moskowitz & Grinblatt (1999) discovered, that different industries also display momentum in returns. They divided equities into 20 industry-based portfolios and examined whether investing in past winner industries and selling past loser industries could be profitable strategy. The results were exhaustive. All industries exhibit momentum and moreover, once controlling returns with industry momentum, momentum investing strategies turned out to be significantly less profitable, hence authors argued, that industry momentum is the driving force behind the momentum effect on individual stocks.

Novy-Marx (2012) proved in his study, that momentum is primarily driven by the past success of the company. Firms' performance in the past 12 to 7 months before portfolio formation is the main factor behind abnormal returns. Moreover, he argued, that strategies based on the recent past generate positive returns but are significantly less effective in terms of returns compared to the strategies based on intermediate horizon past performance, especially among large and liquid stocks. These results also hold for commodities, currencies and equity indices.

The reasons behind momentum anomaly are many. Jegadeesh and Titman (1993) suggested that the main reason behind momentum anomaly is investor overreaction. They argued that at first, stock market overreacts when investors are buying past winner and selling losers but after some time stock prices tend to return to their long-time averages according to mean-reversal. They also pointed out that investors have tendency of underreact to news on short-term prospects and overreact to news concerning about long term valuation and success of underlying company. Similar explanations for momentum were offered by Barberis, Shleifer, and Vishny (1998), According to whom momentum was driven by behavioral issues, investor underreaction and overreaction to certain news. Daniel, Hirshleifer and Subrahmanyam (1998) came up with a similar conclusion. According to them, investor over- and underreaction is based on two psychological biases: investor overconfidence concerning private information and biased self-attribution.

Another aspect regarding returns of momentum anomaly was provided by Johnson (2002). He argued that momentum returns are nothing more but a reasonable payoff for the risk investor is taking. Moreover, deviations in stochastic expected growth rates of companies' cash flows account partly for the momentum effect. Keim (2003) took a more pragmatic view on momentum anomaly. As momentum portfolios require frequent rebalancing, he suggested that whatever the reason behind momentum returns was, in reality, high trading costs of momentum strategies will incrementally derogate most of the returns of different momentum strategies. However, Korajczyk and Sadka (2004) pointed out that even after considering transaction costs and the price impact of trading, momentum strategies stayed profitable. Another interesting finding was that equal weighted portfolios performed best before trading costs and worst after trading cost compared to value-weighted and liquidity weighted portfolios.

2.1.4. Accruals

Accruals anomaly, also known as earnings quality anomaly, was firstly introduced by Sloan (1996) who argued that investors tend to over-value companies with high accruals. His results indicated that accrual-based earnings performance exhibited lower persistence than earnings performance attributable to actual cash-flows. The so-called "earnings fixation" hypothesis of Sloan assumed that stock prices act as if investors fixate on earnings and moreover, as if prices do not fully distinguish between different characteristics of accrual and cash-flow components of the earnings. Thus, companies with relatively high level of accruals tend underperform in terms of stock returns, and vice versa, companies with relatively low level of accruals tend to generate positive abnormal stock returns around the future earnings announcements. In other words, the accruals anomaly stems from a negative relation between accounting accruals and future stock returns. Sloan suggests that low accruals is a sign of high real cash-flow based earnings, whereas high accruals can be a result of some accounting practice. Therefore, a portfolio that takes a long position on companies, which have high cash-flow-based earnings relative to accruals and a short position in companies which have low cash-flow-based earnings and high accruals, should generate abnormal returns.

More recent study of Lafond (2005) strongly advocate the persistence of accruals anomaly. He investigated the returns implications of accruals in 17 countries between 1989 and 2003. Remarkably, he documented significant results in 15 of the 17 countries. Author concluded that the accruals anomaly was a global returns phenomenon. Lev and Nissim (2010) obtained similar kind of results. They argued, that due to the high costs of information and transactions, individual investors are not able to profit from accrual anomaly, which is partly the reason the anomaly still persists, and its magnitude has not declined over the time. However, their study proved, that accruals anomaly is exploited by some active institutional investors in their trading, but still the magnitude of accrual-based trading is quite small. The authors suggested that when taking these facts into consideration, accruals anomaly persists and will probably endure. On the other hand, Mohanram (2013) clarified, that if the mispricing of accruals is the key factor behind accruals anomaly, the better information about the expected future accruals should diminish such mispricing. Thus, when analysts predict future cash-flows, they implicitly predict accruals, therefore precise forecasts on cash-flows should help to reduce the mispricing of accruals. Empirical results suggested that accrual anomaly generated significant abnormal returns until 2002 and since then anomaly has weakened. Bender and Nielsen (2013) stated that earnings quality signal stopped working in mid-2000s but has revived since the end of 2008. They also notified that earnings quality signal worked especially when investing strategy was driven by stock selection, hence earnings quality would be an alpha signal, not necessarily a risk factor, in cross section of stock returns.

A fundamental reason behind accrual anomaly is suggested to be the earnings fixation hypothesis reviewed by Sloan (1996). Another evidence concerning accruals anomaly was found by Ball, Linnainmaa and Nikolaev (2016). They figured out that after controlling cross section of stock returns for cash based operating profitability (COP), accruals was no longer significant predictor of returns. On the other hand, Detzel, Schaberl and Strauss (2017) proposed that accruals anomaly differs from investment and non-investment-related components. They revealed that investment accruals explain the cross section of stock returns better than accruals as whole. Moreover, this factor’s returns are negatively forecasted by the sentiment, whereas results for non-investment accruals are the opposite. The results also indicated that cash profitability absorbs only non-investment accruals in the cross section of stock returns and economy-wide investment accruals do not predict stock returns while other accruals do. The authors concluded that accrual anomaly should be divided in two: a risk factor of investment accruals and a mispricing phenomenon of non-investment accruals.

2.1.5. Net issuances

Net share issuances anomaly has also awoken sound amount of research. The behavioral interpretation behind this anomaly is the fact that companies tend to issue equity when its stock is over-valued and therefore expected return of the stock is low. On the other hand, companies tend to repurchase stocks, retire equity, when its stock price is undervalued. Therefore, long run abnormal returns are believed to be dependent on net share issuances, thus post-seasonal-equity-offerings (SEO) and post–stock merger long run returns should be abnormally low, whereas post-share repurchases long run returns should be abnormally high. (Pontiff & Woodgate, 2008)

Ikenberry, Lakonishok and Vermaelen (1995) examined long-run firm performance after share repurchases programs between 1980–1990. They recorded average abnormal return of 12.1% for four-year buy-and-hold portfolio formed after the initial repurchase announcement. They also pointed out that for value stocks the average abnormal return was 45.3% after repurchases and for glamour stocks there was no positive abnormal returns recorded after repurchases of stocks. These results were consistent with Loughran and Ritter (1995) who examined the returns after share issues. Their results provided evidence that returns of companies which have issued stock either through initial public offering or seasoned equity offering between 1997–1990 have been poor compared to non-issuing firms for five subsequent years after the offering date.

Pontiff and Woodgate (2008) investigated the net effect of share issuances in cross section of stock returns and recognized a negative relation between net stock issuances and average returns. They found out that in the post-1970 time period, both annual and 5-year share issuance are significant factors in explaining future stock returns. The statistical significance of annual share issuance-factor was greater than previously displayed predictabilities of

B/M, size and momentum. Pontiff and Woodgate concluded, that an opportunistic view on capital structure exists, meaning that insiders exploit the under- or over-valuation of stock price. They also examined pre-1970 time period, finding that 5-year share issuance factor was statistically insignificant and annual share issuance factor was statistically significant only for one year holding period. Explanation for the differences between time periods was namely because before 1970 there was significantly less share issuances. Similar results were documented by Lee (2013). He underlined that financial market anomalies are mispricings because companies tend to act as arbitrageurs by issuing shares when they expect decrease in the stock price and by repurchasing stocks when they expect increase in the stock price.

Fama and French (2008) also found anomalous returns associated with net stock issuances. In their research repurchase of stock was followed by strong positive abnormal return. In addition to this, the most extreme quintile of stock issues displayed a strong negative abnormal return. However, after controlling the returns for size and B/M, abnormal returns for less extreme positive stock issues portfolios were somewhat positive. This implicated that stock issuances and repurchases returns were not fully consistent with previous studies.

2.1.6. Low risk

Investors are assumed to be risk averse in nature, meaning that they seek to minimize the risk they have to endure in order to obtain certain expected return. Variance is a measurement of stock risk. Markowitz (1952) concludes expected return being desirable thing whereas variance undesirable thing in investing. This composition led to Modern Portfolio Theory (MPT) according to which investors maximize the expected returns at a given level of market risk, therefore enabling investor to form so-called “efficient frontier” of possible allocation choices of the portfolio. With this in mind, there has been some anomalous returns generated with low risk stocks that violate the basic assumptions of MPT. The total risk of specific stock can be decomposed into systematic or market risk and idiosyncratic risk or firm-specific risk. Previous researches have proven that by allocating capital into low risk stocks, measured either by beta coefficient or variance of returns, an investor could have earned abnormal risk-adjusted returns.

Beta coefficient (β) of CAPM is a firm specific coefficient of risk, which measures a company's exposure to market risk.

$$\beta = \frac{COV(R_i, R_m)}{VAR(R_m)} \tag{3}$$

Black, Jensen and Scholes (1972) found out that the expected linear relationship between stock returns and beta of CAPM was inconsistent. They noticed that excess return of a stock did not always implicitly result in equally high beta coefficient, thus security market line appeared to be too flat compared to one implied by the CAPM. The time-series regression results they obtained between 1947 and 1965 indicated that high beta securities had significantly negative intercepts whereas low-beta securities had significantly positive intercepts, meaning that low-beta stocks had outperformed high-beta stocks.

Blitz and Vliet (2007) examined low-volatility anomaly among large cap stocks between 1986 and 2006 in U.S, Japan and Germany. The results showed that stocks with low volatility generate higher risk-adjusted returns. The difference in average returns between top and bottom decile portfolios, thus extreme high volatility and extreme low volatility, was 5.9% annually. Another compelling fact was that the annual alpha spread of global low and high volatility portfolios was 12%. Moreover, the Sharpe ratios and Fama-French alphas seemed to steadily decline in volatility. The authors also found that low risk portfolio has a low beta of 0.56 with a positive annualized alpha of 4%. Furthermore, betas increased monotonically for the consecutive decile portfolios. This indicated that beta and volatility are related risk measures, thus beta coefficient obviously negatively related with future stock returns. Blitz and Vliet (2007) offered also explanations for the irrationality that investors tend to overpay for risky stocks. According to their reasoning, leverage restrictions, inefficient two step investment processes and behavioral biases of private investors could be explanations for this phenomenon.

Cederburg and O'Doherty (2016) suggested investors to approach a possible bet against beta strategy with caution. Their empirical results indicated, not only that the differences in conditional alphas across high- and low-beta portfolios are substantially smaller in economic magnitude and statistically insignificant, but also that differences in risk-adjusted returns between high- and low-beta portfolios are largely due to biases in unconditional performance measures. Bali *et al*. (2017) explained that beta anomaly is mainly driven by the demand of lottery like stocks. Investors tend to be fascinated by illiquid stocks with high probability of substantial short-term upward movements. These movements were at least partially generated by beta. Massive demand of these lottery-like stocks pushes their prices up, thus expected future returns decrease, which leads to poor performance of these high beta stocks. Beta anomaly disappeared, after controlling the returns for this lottery demand. Moreover, Liu, Stambaugh and Yuan (2018) argued that beta anomaly is caused by idiosyncratic volatility (IVOL) of individual assets. Relation between IVOL and alpha is positive among underpriced stocks and negative among overpriced, high beta, stocks. Their empirical evidence suggested, that this strong negative relation combined with the positive IVOL-beta correlation produces beta-anomaly. Beta anomaly was insignificant after controlling results for either IVOL or excluding overpriced stocks with high IVOL.

Frazzini and Pedersen (2014) proved that betting against beta has generated abnormal returns between 1926 and 2012. They formed BAB (betting against beta) factor which took a long position on low beta stocks and short position on high beta stocks. In addition to this, researchers levered the low beta portfolio and de-levered the high beta portfolio in order to generate a market neutral BAB factor. Although BAB factor generated risk-adjusted excess returns, in order to profit from the BAB factor, one had to lever up the low beta portfolio until preferred risk-return feature. Interestingly, authors claim that Warren Buffett's company Berkshire Hathaway bets against beta by buying low beta stocks instead of low volatility stocks and then applies leverage into portfolio.

Baker, Bradley and Wurgler (2011) investigated the returns generated by low risk by forming low risk portfolios based on beta and lagged volatility of stocks. Authors summarize, that it makes no different, whether risk is defined as beta or volatility and moreover, whether including only large cap stocks or all of them in the portfolio formation. Low risk portfolio consistently outperformed high risk portfolio over the period between 1968 and 2008 in the U.S. stock market. In their research, over the beforementioned period 1 dollar in low volatility portfolio resulted in 10,12 dollars when taking inflation into consideration whereas one dollar in high volatility portfolio declined into less than 10 cents. Furthermore, one dollar in low beta portfolio resulted in 10,28 dollars and one dollar in high beta portfolio decreased into 64 cents.

2.2. Calendar anomalies

In previous studies, certain time-dependent patterns have found to exists in stock market returns. These time-dependent patterns in returns, also known as calendar anomalies, indicate that the absolute return of a specific stock may not be dependent on the fundaments of the company, but the time of the year. They are seasons within a year that generate anomalously high returns compared to the remainder of the year.

2.2.1. Half-year anomaly

Sell in May -effect, Halloween-effect, or in other words half-year anomaly, is not quite as well examined anomaly as are momentum or value anomalies. Researches before the turn of the century were scarce and even though some engrossing evidence has emerged concerning the anomaly, comprehensive studies about the effect are quite few. To my best knowledge, one of the best known and first throughout study on half-year anomaly was conducted by Bouman and Jacobsen (2002). They examined on whether stocks perform better when entering with a long position at the end of October and selling stocks at the end of April each year. Time period of the investigation was from 1970 to 1998 and the research included 37 market indexes of different countries all around the world. Their results were persuasive. The half-year anomaly was present in both developed and in emerging markets. Moreover, the period from November to April resulted in large returns in almost every country, whereas the average returns between May and October were insignificant and often close to zero. In addition, the inclusion of January dummy did not make a significant difference in results, proving that sell in May was not just a January effect in disguise. Bouman and Jacobsen also suggested, that one possible reason behind the seasonality could be behavioral factors such as change in risk aversion of investors during summer vacations.

Jacobsen and Visaltanachoti (2009) examined half-year anomaly within U.S. stock markets between 1926 and 2006. They focused on different sectors and industries within economy in their research. They found out that in more than two-third of the industries and sectors half-year anomaly was statistically significant. Even changes in liquidity measures (Pastor and Stambaugh, 2003) and well-known risk factors did not explain the anomaly. Authors also underlined that effect was especially strong in sectors related to production and absent in sectors related to consumer consumption. Similar results were obtained by Andrade, Chhaochharia and Fuerst (2013). They studied half-year anomaly in 23 developed, 12 emerging and 2 frontier markets between 1998 and 2012. They conducted first throughout out-of-sample study concerning half-year anomaly in order to avoid possible problem of data snooping. The Sell in May -effect was pervasive among stock markets. They recorded on average 10 bps (basis points) higher returns for November-April period compared to May-October period. Therefore, recorded out-of-sample persistence pointed out, that Sell in May -effect was an anomaly to take into consideration and not merely a statistical fluke. Results also underlined that not only was the half-year anomaly present in equity risk premium but also in the size, value, FX, carry trade, equity volatility risk and credit risk, meaning that there was many profitable trading strategies inside the Sell in May -effect. Another research advocating the Sell in May -effect was conducted by Zarour (2004) on Arab markets. He testified statistically significant half-year anomaly in 7 out of 9 equity markets in the Middle East. Moreover, results were robust even after controlling for January effect. Lean (2011) found somewhat similar results in the Asian markets concluding, that half-year anomaly might also be profitable for investor in the Asian markets. He used traditional dummy regression with and without controlling January, but also conditional variance models of GARCH, EGARCH and TARCH. According to linear regression model and conditional variance model's half-year effect was widely present in Asian markets. The only market that did not exhibit half-year effect was Hong Kong.

There has also been robust empirical evidence against the effectiveness of half-year anomaly on cross section of average stock returns. Maberly and Pierce (2004) investigated whether the half-year anomaly is caused by outliers in the data. They included dummy variables for October 1987 market crash, also known as Black Monday, when stocks fell on average by 20 percent as well as for market crash in August 1998, when Russian government announced moratorium on debt repayments, which caused stocks to fell on average 15 percent and resulted in collapse of the hedge fund Long-Term Capital Management. The authors also created a dummy variable for January. After adjusting returns to the impact of these outliers, they found that the market inefficiency known as half-year anomaly disappeared in the U.S. markets. However, during bear market years, most of the decline in stock prices usually took place in the period between May to October. Jamil and Hayati (2018) explored the occurrence of half-year anomaly on the Indonesian Stock Exchange and came up with the similar conclusion that sell in May and go away was not a good advice. They pointed out that there was no difference in stock returns between May-October and November-April periods among large cap or small cap companies. Dichtl and Drobetz (2015) implemented bootstrap simulation method in order to investigate half-year anomaly and avoid possible data snooping biases. Their results were also against the anomaly with respect that anomaly has weakened in recent years.

Jacobsen, Mamun and Visaltanachoti (2005) conducted a study on U.S. stock market between 1926 and 2004 on half-year anomaly within decile factor portfolios based on company's size, book-to-market ratio, earnings-price ratio, cash-flow-to-price ratio and dividend yields. Their results indicated that half-year anomaly was statistically significant in all factor portfolios and that January effect was mostly concentrated on size and book-to-market portfolios. In dividend yield portfolio, seasonality was stronger within low dividend yield stocks. January effect differed from half-year anomaly and half-year anomaly was unrelated to well-known anomalous behavior of portfolios formation criteria. However, after adding general market index as explanatory variable, the subsequent significance of half-year anomaly within factor portfolios disappeared completely, whereas January effect remained statistically significant in small cap portfolio and BE/ME portfolio.

Explanations for half-year effect vary from statistical fluke to behavioral finance. The seasonal affective disorder (SAD), described by Kamstra, Kramer and Levi (2003), could be one possible explanation for half-year effect. According to them, SAD effect is a condition, that affect people during seasons of relatively fewer hours of daylight, which ultimately results in increased rates of depression. Moreover, depression and increased risk aversion has a clear linkage, thus seasonal variation in length of the daylight can be conflated to seasonal variation in equity returns. Authors wind up with empirical evidence that strongly supports this theory. According to the evidence, patterns at different latitudes and in both southern and northern hemisphere provided a sound evidence of the link between seasonal depression and seasonal variation in stock returns. Thus, higher latitude markets showed unambiguous SAD effect whereas results in the Southern hemisphere were six months out of phase. These results were statistically significant even after controlling the influence of other environmental market factors and market seasonals. The linkage between half-year anomaly is that during the half-year anomaly time period, investor is more risk averse, thus capital allocation should be more rational and effective among investors and therefore levels of moral hazard and asymmetric information are lower. Meschke and Kelly (2010) pour could water on the SAD effect and suggest, that SAD effect is substantially driven by an overlapping dummy variable specification, a statistical bias and higher absolute returns around the turn of the year. They replicated the study of Kamstra *et al*. (2003) and found out, that SAD model did not have link to seasonal patterns in depression found in societies. Moreover, the prevalence of SAD and stock returns had no relation according to the results. Another valid explanation for the half-year anomaly could be the beforementioned impact of outliers on returns (Maberly and Pierce, 2004).

When exploring the possible explanation for half-year effect, Bouman and Jacobsen (2002) found out that interest rates, trading volume and seasonality of news could not fully explain the anomaly. Explanation of sector-specific anomaly was also ruled out by empirical evidence. Vacations was statistically significant explanatory variable and with respect to the timing of vacations, the significant relation remained on monthly and semiannual level. However, arbitrageurs could trade this effect away.

2.2.2. The January effect and the Month-of-the-year effect

Perhaps the most familiar calendar anomalies is the January effect. Many academics and investors have found that especially in January stock returns tend to be superior compared to the rest of the months. Many have suggested that it is caused by tax-loss-selling in the end of the year, and re-allocation of capital in the portfolio towards next year (e.g., see Chen and Craig, 2018; Thaler, 1987).

One of the first researches to reveal the January effect was conducted by Rozeff and Kinney (1976). They examined capital market seasonalities in U.S. stock markets between 1904 and 1974 and noticed that the most outstanding feature among seasonalities is the higher mean return of the January distribution of returns relative to other months. However, in addition to January, they also found relatively high returns in July, November and December. Authors used two-parameter capital asset pricing model to estimate risk premiums of different months ending up with result that January had also relatively higher risk premium, thus higher mean returns were partially offset by higher risk.

Keim (1985) also documented the effect of January on U.S. stock returns. By investigating the relation between dividend yield and stock return. His results strangely indicated that dividend yield effect had a significantly positive coefficient that exhibited January seasonal. The study pointed out that much of the relation between dividend yield and stock return was due to significant non-linear relation in January even after controlling for firm size. Furthermore, returns in January were too large and significant for being explained solely as tax brackets associated with after-tax asset pricing models. Somewhat similar results were reported by Haugen and Jorion (1996) who found that the January effect had not disappeared from U.S. markets nor had it diluted. However, they concluded that attempts to exploit the January effect display significant amount of risk and therefore anomaly may persist in time.

Cooper, McConell and Oytchinnikov (2005) noticed that the January effect exists but they also came up with so called the other January effect. This was due to the notification that January was a significant predictor for the following 11 months' returns, meaning that if stock returns in January were substantial it implicated that returns in the forthcoming year would also be better. This effect persisted even after controlling results for macroeconomic variables, The presidential cycle in returns and investor sentiment. Moreover, the results persisted among small and large cap stocks and even among value and glamour stocks.

Kramer (1994) investigated the January effect and macroeconomic seasonality. In his investigation, he used CAPM model and model based on arbitrage pricing theory (APT) with five systematic risk factors closely related to asset markets. These factors were default risk, derived as difference between return of corporate bonds and government bonds, maturity risk, derived as difference in returns between of government bonds and treasury bills, inflation factor, obtained from residual of integrated moving average model and consumption factor, derived as growth rate of consumption and market factor. The results indicated that January effect was present in low priced companies and furthermore, that the CAPM with seasonal expected return did not account for it. However, multifactor model with seasonal risk and risk premia accounted for January effect, thus indicating that shifts in the expected return are behind January seasonal in low priced companies.

The results obtained by Patel (2016) in his research between 1997 and 2014 indicated, that January effect did not exist anymore in global stock markets. They also examined whether macroeconomic environment matters when it comes to January effect and found out that no matter if markets are bullish or bearish, no statistically significant January effect existed.

The possible reasons behind the January effect are many. Private and public placements indicate that investors seem to be over-optimistic on their own skills to replicate former success, especially when sentiment is high. (Hertzel *et al*., 2002) This can be contributed to the notification that afterwards institutional and individual investors tend to re-evaluate their portfolio allocation in January, which could be a one driver behind the anomaly. In addition to this, at the end of the year investors usually receive annual reports from mutual funds, gain bonuses and prepare for taxes, which may lead to re-allocation of portfolios resulting in superior returns in January. (Doran, Jiang & Peterson, 2008)

Tax-loss-selling is one explanation behind the January effect. Branch (1977) emphasizes how tax-loss-selling drives investors to sell stocks in December. This decreases stock returns and prices, which ultimately leads to a superior stock returns via increase in stock prices in January. Similar findings where obtained by Reinganum and Shapiro (1987) on London Stock Exchange. However, Jones, Pearce and Wilson (1987) provided empirical evidence regarding the taxation explanation and concluded that the January effect was statistically significant even after controlling for taxation effect. Selvarani and Jenefa (2009) examined January effect among other calendar anomalies within National Stock Exchange of India, where fiscal year end is in March and still discovered January effect among other effects. Correspondingly, they also found April effect.

Lakonishok, Shleifer, Thaler and Vishny (1991) investigated funds invested by pension fund management companies and noticed that these companies tend to exclude poorly performed equities from their portfolio at the end of each quartile especially at the end of fourth quartile. Motivation behind this action seemed to be so-called *window dressing* -strategy, in which reallocation is done at the end of each quartile in order to make portfolio look better.

Malkiel (1999, 248) also notified presence of the January effect especially among small capitalization stocks. According to him, this anomaly is mainly caused by the tax-loss-selling, which appears mostly within small capitalization stocks, because they are much more volatile and less likely to be in tax-exempt for large institutional investors or pension fund portfolios. Nevertheless, the January effect is not an exploitable anomaly for normal commission paying investor, because of the transaction costs related to commissions and bid-ask spreads. Fortune (1991) argued that tax-selling hypotheses was not consistent with the efficient market hypothesis. Thus, investors, with no capital gain taxes should recognize the abnormally low prices caused by tax-selling and therefore, become buyers of such oversold stocks, thereby driving their prices back towards their equilibrium price.

Month-of-the-year effect refers to the notion, that there are differences between monthly mean stock market returns. Marrett and Worthington (2011) examined month-of-the-year effect with the Newey-West regressions in Australian stock markets and different industries. They noticed, that returns where significantly higher during the months of April, July and December. In addition to this, Month-of-the-year and small cap effect combined resulted in systematically higher returns during January, August and December. Moreover, they discovered that the most substantial industry level Month-of-the-year effect were in telecommunications industry, where January returns were more than thirty-three times higher with respect to other months. Raj and Thurston (1994) investigated monthly returns based on the turn of the year effect in New Zealand, where fiscal year ends in March. Their results indicated that tax-selling theory did not hold, as there were no superior returns in April despite the ending of a fiscal year. Moreover, there was no anomalous returns in any month according to their findings. Choudhry (2001) examined the existence of the Month-of-the-year effect within stock market returns within pre-world-war 1 period between 1870-1913. Choudhry employed non-linear GARCH model and asymmetric GARCH-GJR model, which takes the leverage effect of stock market into account, in order investigate Month-of-the-year effect. Leverage effect refers to the notion that volatility is often asymmetric, thus falls are often larger than rises in stock prices. His results indicated a strong January effect and presence of Month-of-the-year effect in other months as well.

Keloharju, Linnainmaa and Nyberg (2016) examined a strategy, in which a long and short position was taken based on stocks' historical same-calendar-month returns. With this strategy, an investor was able to generate annual mean return of 13%. They formulated a cross-sectional regression on stocks listed in NYSE, Amex and NASDAQ and noticed, that a traditional strategy opening a long and short positions on 15 different anomalies based on their historical same-calendar-month returns , earns approximately 1,88% per month with a t-value of 6.43, whereas an alternative strategy based on other-calendar-month premiums earns even slightly negative absolute returns. Moreover, according to authors seasonalities are stemming saliently from systematic risk factors associated with company characteristics such as size, dividend yield and industry. This is due to the notion that seasonalities are strongly present in returns of well-diversified portfolios and the variance of the strategy trading seasonalities is five times higher that it would be when taking into account only idiosyncratic risk. The authors conclude that same-calendar-month seasonalities within 15 anomalies are economically significant and appear not only in stocks but also in commodities, whereas other-calendar-month returns for anomalies turned out to be a poor prediction about the future returns. Remarkably, when the authors added a seasonality factor to an investment opportunity set including momentum, size, value and market factors, the Sharpe ratio increased from 1.04 to 1.67. This increase was almost as substantial as when adding momentum, value and size factors into an investment opportunity set consisting of only market factor.

3. THEORETICAL FRAMEWORK

This section will go through the theories behind this thesis. These theories are sort of guidelines for reader to understand the basic assumptions behind the empirical results. The surrounding world may not be precisely in line with these theories, rather they are only attempting to somehow describe the market behavior and price formation on different assets. Nevertheless, it is essential to understand these theories in order to make critical statements on whether there are veritable deviations from them.

3.1. Efficient market hypothesis

Efficient market hypothesis (EMH) is a widely known theory about market efficiency and its different forms (Fama 1970, 1965). EMH assumes, that markets are efficient, thus all available information is already included in the asset prices and a strategy that can constantly generate excess returns does not exist. Moreover, Fama argues that when markets have many rational, well-informed and intelligent investors, securities will be appropriately priced and they therefore reflect fully all available information. In other words, prices are independent, identically distributed random variables (i.i.d). Therefore, expected returns of a portfolio formed with proper analysis and information will not bypass the returns of the relevant benchmark index. According to EMH, fierce competition between large number of intellectual participants lead to a situation in which the price of an asset reflects all events and information already occurred in the markets and furthermore, even events and information that markets expect to take place in the future. Thus, at any given point of time, market price of a security is a valid estimate of the intrinsic value of the underlying company. As well-informed investors grow in number, simultaneously the liquidity of the assets and market mechanism pricing them enhances.

Fama (1970) describes that there are three forms of market efficiency. The first one is called *weak form* market efficiency, which indicates that all past market prices and data are fully reflected in security prices. Therefore, one should not be able to generate abnormal returns by means of technical analysis. The second one is *semi-strong* from of market efficiency, in which all publicly available information is already included in stock prices. This implies that even with fundamental analysis, an investor cannot beat the market return. *Strong form* market efficiency asserts that all information, public or private, is fully reflected in stock prices. Therefore, one cannot generate abnormal return even by exploiting insider information. As Malkiel (1999, 13) concludes that investor is better off when not trying to beat the market, but satisfies with the board market index with low costs.

The studies conducted on market anomalies carry the same message that markets are not efficient and there are systematically abnormal returns available. According to Jensen (1978), these studies provide a powerful stimulus and act as reminder for us that there are inadequacies in our current state of knowledge. For this thesis, EMH is an especially intriguing hypothesis, hence the main object of the empirical investigation in this thesis is to exploit some of widely known deviations from the market efficiency in order to beat the market return. However, as mentioned before, usually when anomaly is published by the academics, it disappears because large group of margin investors corrects the mispricing. Hence, market efficiency can be debated to enhance all the time as we receive more information about the market behavior. On the other hand, Paulos (2003, 187-188) concludes that if every investor would rely on market efficiency there would not be market efficiency because there would not be anyone to analyze securities and correct the mispricing in the market.

3.2. Behavioral finance

When considering the anomalies and their explanations, theory and former studies mentioned in the literature review often refer to behavioral factors as being one reason behind deviations from market efficiency. Ultimately what this means is that if we can consider all individual investors to be rational and weigh properly their investment decisions with all available information, deviations would not exist. However, often this is not the case. Investors tend to make irrational decision when it comes to allocating their funds. This irrationality has given rise to behavioral finance. Behavioral finance attempts to answer the questions regarding investor behavior, capital allocation and risk-adjusted differences in stock returns. In the context of this research, behavioral factors may accelerate fundamental anomalies and seasonalities inside these anomalies or even in some instances incrementally generate them. This section offers a holistic view on behavioral factors that may be behind nested anomalies.

3.2.1. Limits to Arbitrage

In behavioral finance, deviations from fundamental value of stock are caused by the presence of investors who are not fully rational. Basic question is, why anomalies exist and why are they not eliminated by arbitrageurs? Limits to arbitrage describes the constraints and limitations arbitrageurs face. These factors may result in a situation where arbitrageurs fail to bring prices close to the intrinsic or fundamental values described by standard models. In a way, limits to arbitrage can be viewed as a force that prevents rational investors to fully exploit these deviations from fundamental value and adjust the mispricing. As Warren Buffett concludes: “Markets can stay irrational longer than you can stay solvent.” (Hämäläinen & Oksaharju, 2016)

Leverage constraints faced by arbitrageurs may be one driving force, that keeps the prices from adjusting. Arbitrageurs are faced with risk driven by irrational investor, which is that prices may not adjust to fundamental values in time for arbitrageurs, which may lead to situation where arbitrageur faces margin call because of the leverage. Therefore, it creates constraint for leveraging of arbitrageurs because of the risk of losses. Furthermore, as irrational investors noise-traders may cause fluctuations in stock price that could result in more substantial mispricing rather than closer to fundamental value. (Cromb & Vayanos, 2010)

Another limit to arbitrage causing the anomalies investigated in this thesis in *time-horizon*. This might happen in a situation when mutual fund manager has an investing strategy exploiting market mispricing that would result in substantial returns in the long run. However, because of the investors demand for returns in the short run, manager may be forced to sell the position when facing short run losses, thus mispricing will endure. (Shleifer and Vishny, 1997)

Benchmarking can also be seen as a limit to arbitrage and one reason for low-risk and low-beta anomalies to exist. This results from the fact that typically institutional investors have a certain mandate to outperform certain fixed benchmark index, thereby discouraging arbitrageurs actions in some asset classes and declines demand towards some highly yielding assets. (Baker, Bradley, and Wurgler, 2011) Respectively, high-risk stocks can be *hard-to-arbitrage* stocks represented by small capitalization, young, illiquid, non-dividend paying and unprofitable companies (Baker and Wurgler, 2007).

Implementation costs are also viewed as a factor causing anomalies to persist. Transaction costs stemming from rebalancing and cost for borrowing stock for short selling may dilute the profits gained by arbitrageur. Prices for borrowing a stock are usually low, but there might be situations when they are higher and, in some instances, it might be even impossible to short sell a stock. In addition to this, there might be legal constraints for some institutional investors that prohibit short selling. (Barberis & Thaler, 2003)

3.2.2. Non-fundamental demand

In addition to limits to arbitrage, there are some behavioral factor driving non-fundamental demand of stocks. *Lottery demand* described by Bali *et al*. (2017) is suggested to be one possible factor affecting non-fundamental demand for high volatility stocks. *Representativeness heuristic* is investors tendency of assuming that one thing means another. Investors may conclude that a company that has performed well in the past will keep on performing well. (Shiller, 2000, 144) This might lead to deviations from market efficiency and for example, momentum investors can exploit this behavioral bias.

Another factor behind non-fundamental demand is *overconfidence.* According to Baker, Bradley and Wurgler (2011) overconfidence might be reason behind anomalies like bet against beta. This is the situation, when investors put too much trust on their own abilities to predict outcomes. Moreover, overconfidence with constraints on short selling might lead to a situation where overoptimistic investors actually set the price for a stock thereby leading to low future returns. (Miller, 1977) *Anchoring* is yet another behavioral bias investor tends to make in the stock markets. This means the tendency to make investment decisions based on assumptions or information received in the past rather than adjust the decision with new information. For example, investor may have a “right” price for the stock in their minds based on the past price formation and therefore, they can consciously ignore new information about the underlying company. (Hämäläinen & Oksaharju, 2016, 150)

Loss aversion of individual investors can cause deviations from stocks' fundamental value. Investors do not like to admit their mistakes and therefore tend to hold on for losses in hope that someday prices will rise again. In some cases, investors even double up their initial investment as stock drops in value. This leads to distortion in stock prices. (Damodaran, 2002, 29) *Herd behavior* is also one potential explanation accelerating mispricing of stocks. Even rational investors tend to participate in herd behavior when they take other people's opinions into account. Herd behavior produces group behavior in the markets which is often irrational and leads to deviations from market efficiency. (Shiller, 2000, 151) Investors also seem to suffer from *information overload*. This leads to tendency of reacting to the latest piece of news, which can create mispricing of certain assets and ultimately results in a lower return for investor. (Damodaran, 2002, 29)

3.3. Portfolio performance measures

In this section, I will go through portfolio performance measures used in this thesis to examine whether the portfolio returns could be stemming from elevated risk associated with them. When it comes to individual stocks, risk can be divided to systematic and unsystematic risk as mentioned before. The notable distinction between these are that unsystematic risk is a firm specific risk which we can diversify away whereas systematic risk concerns all wide range of assets. The assumption of a well-diversified investor behind traditional asset pricing theories leads to the assumption that only systematic risk matters because unsystematic risk is diversified away. In this thesis, risk-adjusted performance of factor portfolios is measured with Sharpe ratio and Adjusted Sharpe ratio which both consider systematic and idiosyncratic risk of individual portfolio.

3.3.1. Sharpe ratio

Sharpe (1966) came up with a risk measure called Sharpe ratio (SR). This risk measure explicitly describes the risk-adjusted performance of portfolio. Sharpe ratio is very widely used performance measure and therefore, it is also utilized in this thesis to reflect the total risk associated with portfolio returns. To be more specific, the ratio measures the excess return of a portfolio relative to its volatility, thus indicating the level of risk taken in order to achieve excess return over the risk-free rate.

$$Sharpe\ Ratio = \frac{R_p - R_f}{\sigma_p} \tag{4}$$

The higher the Sharpe ratio, the better. In the equation (4) R_p is the return of the portfolio, σ_p the volatility of the excess returns of the portfolio, and R_f the risk-free rate. However, Sharpe ratio has its pitfalls. It assumes that returns are normally distributed and therefore, it is not necessarily valid method when returns happen to have fatter tails than normal distribution. Also, the Sharpe ratio can result in misleading conclusion if the distribution of returns is skewed. This is fairly common in financial data which can be caused by volatility clustering, for example. (Ledoit & Wolf, 2008) Sharpe ratio is also often criticized for oversimplifying the concept of risk. This stems from the fact that the Sharpe ratio does not make distinction between upside and downside movements around the mean. Therefore, it penalizes the upside potential, which from the viewpoint of an investor is desirable feature in a stock. (Leivo & Pätäri, 2011)

3.3.2. Adjusted Sharpe ratio

To fix the drawbacks of traditional Sharpe ratio, adjusted Sharpe ratio (ASR) was introduced by Pezier and White (2006). Unlike Sharpe ratio, adjusted Sharpe ratio takes skewness and kurtosis of the distribution into consideration. Adjusted Sharpe ratio increases or decreases, depending on the value and sign of skewness, thus increasing when positive and decreasing when negative. In order to enhance the robustness of the performance measurement in this study, ASR is employed.

$$ASR_i = SR_i[1 + \left(\frac{S}{6}\right) * SR_i - \left(\frac{E}{24}\right) * SR_i^2]$$

(5)

SR stands for traditional Sharpe ratio, S for skewness and E for excess kurtosis of the distribution of data. Excess kurtosis is calculated as kurtosis of the distribution of the data minus 3. The basic assumption behind ASR is the fact, that investors prefer positive skewness and positive excess kurtosis. Therefore, ASR contains a penalty factor for negative skewness and positive excess kurtosis. Unlike the Sharpe ratio, ASR does not penalize the upside potential of returns. If returns are normally distributed, thus $S=0$ and $E=0$, ASR results in same value as normal Sharpe ratio. Pezier and White (2006) examined portfolio performance and optimization with the Sharpe ratio, ASR and Omega ratio. They used set of genetic algorithms to optimize portfolios in a way that maximize beforementioned three risk-adjusted performance criterion. They found out that optimization resulted in an extreme allocation of portfolios and furthermore, deviations from normal distribution in returns did not have substantial effect on the asset allocation between equities, bonds and commodities. Eling (2008) observed risk-adjustment measures in a broad scale. He argued that performance measure is not critical when it comes to fund evaluation and that normal Sharpe ratio is adequate for analyzing fund performance. Many researchers have end up with the same conclusion. (e.g., see Eling and Schuhmacher, 2006; Pätäri and Tolvanen, 2009)

4. DATA AND METHODOLOGY

4.1. Data

Pre-calculated portfolios for each risk factor and market return data are from Kenneth French's data library[1]. These portfolios are based on CRSP (Center for Research in Security Prices) securities total return data from July 1963 to September 2019. In order to mitigate any possible biases regarding the size of the sample and data mining, all securities in NYSE, Amex and Nasdaq are included in investigation. Based on these exchanges, pre-calculated portfolios are used as proxies for different anomalies.

This thesis utilizes monthly returns data of pre-calculated portfolios based on firm-characteristics of *company size* (SIZE), *book equity to market equity* (BE/ME), *momentum* (MOM), *net shares issues* (ISS), *earnings to price* (E/P), *dividend to price* (D/P), *operating profitability* (OP), *cashflow to price* (CF/P), *accruals* (ACC), *daily variance* (VAR), and *company beta* (BETA) from July 1963 to September 2019. Furthermore, extreme deciles based on these firm-specific factors, thus top and bottom decile are used in in this research. All factor portfolios are based on companies listed in NYSE, Amex and Nasdaq. SIZE factor portfolio is based on monthly data of market capitalization of U.S. companies. BE/ME portfolio is formed based on *t-1* book equity and market equity. OP is based on operating profitability of companies in *t-1*. E/P and CF/P portfolios are based on earnings/cashflow in *t-1* and price in the end of December in year *t-1*. D/P portfolio is based on total dividends paid from July of year *t-1* to June of year *t* per dollar of equity in June *t*. In momentum portfolio, stock must have a price at the end of month *t-13* and moreover a good return for *t-2*. ACC portfolio is based on change in operating working capital per split-adjusted share from fiscal yearend *t-2* to *t-1* divided by book-equity per share in *t-1*. BETA portfolio is based on beta-coefficients estimated using five years or minimum of two years of preceding monthly returns. VAR portfolio is based on the variance of 60 lagged daily returns or minimum of 20 days and ISS portfolio is formed according to change in split-adjusted shares outstanding in yearend of *t-2* and *t-1*. MOM and VAR portfolios are rebalanced monthly whereas others are rebalanced annually. ISS portfolio is formed according to change in the number of split-adjusted shares outstanding between yearends *t-2* and *t-1*.

Overall market return data of NYSE, Amex and Nasdaq is used as market index and the 1-month U.S. treasury bill as a risk-free rate of return. Risk-free rate is obtained from Thomson Reuters DataStream. Recession indicator used in robustness check is obtained from Economic research of Federal Reserve Bank of St. Louis[2]. In addition to this, liquidity measure of Pastor and Stambaugh (2003) is used in factor regressions and to observe the changes in market liquidity. This measure of market-wide liquidity is obtained from University of Chicago's website[3].

Portfolios for each factor are calculated in a way that possible biases are taken into account. Breakpoints for portfolios are calculated in the end of June, thus a possible *look-ahead bias* is considered. Look-ahead bias refers to a situation, where decisions are made based on information that was not available on the time decision making. *Survivorship bias* is also taken into account by including all securities and marking return to zero when a portfolio company has been delisted. Even though portfolios include firms from all three exchanges, the breakpoints of portfolios use only NYSE securities. More information concerning the structure of each individual portfolio can be find from Kenneth French's website[1].

[1] *http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html*

[2] *https://fred.stlouisfed.org/series/USRECM*

[3] *https://faculty.chicagobooth.edu/lubos-pastor/data*

In order to result in a comprehensive understanding on seasonalities within anomalies, wide range of different firm-specific factors are selected. Each factor represents a different quality of underlying company. Size factor provides us insights on whether small cap stocks are superior in terms of returns even when compared to other anomalies. With BE/ME it is possible to conclude on whether company's balance sheet equity value compared to market value provides a signal on the future returns. E/P on the other hand provides us insights on whether earnings-based fundament is a robust indicator of future profits and CF/P offers us a view on cash-flow based valuation and how does this predict future returns. OP is connected to company's overall profitability and its meaning in terms of future stock returns. D/P indicates on whether company's dividends play a major role in predicting future returns. Portfolios based on accruals and net issuances summarizes on whether companies have been profitable or whether they have taken part in operations that have decreased future returns. Portfolios based on variance and beta offers a holistic view on low risk stocks and their performance. Exception among selected portfolios is momentum, which is included in this thesis in order offer modest technical analysis contribution to result.

Table 1 describes the average size of a company in each factor-portfolio and average number of companies in that portfolio. Portfolios are on average large samples of selected anomaly, and therefore the representativeness of the results is rather robust within U.S. stock market. Moreover, with a large quantity of stocks within portfolio it is possible to obtain more comprehensive view on anomaly when large price movements in small group of stocks do not have substantial effect on the overall portfolio returns. More descriptive statistics concerning factor-portfolios data are reported in **Appendix 2**.

Table 1. Descriptive statistics of portfolios.

Portfolios obtained from Kenneth French's Data Library consist of U.S. securities listed in Nasdaq, NYSE and Amex. Lo 10 means bottom deciles of the specific portfolio, whereas Hi 10 describes the top decile. Numbers in this table are average values of portfolios's statistics from the time period between 1963 and 2019.

	Avg. Size of Company in Portfolio (milj.$)		**Avg. Number of Companies in Portfolio**	
Mean	**Lo 10**	**Hi 10**	**Lo 10**	**Hi 10**
SIZE	45	28967	2097	152
BE/ME	3439	481	575	474

OP	302	3668	950	344
E/P	2123	1280	445	327
CF/P	2203	1167	500	325
D/P	3602	2069	211	171
MOM	749	563	374	1485
ACC	1036	684	406	483
BETA	2172	548	417	628
ISS	2029	667	202	464
VAR	6589	207	339	1401

4.2. Methodology

This thesis utilizes deciles of each factor portfolio. Deciles used in this thesis are the top decile, which includes companies with high/low value of desired feature and the bottom decile, which includes companies with opposite values of the desired feature. For each individual factor, long and long-short strategy is calculated from a monthly time-series of returns data. Long portfolio includes top decile and long-short portfolio investigates strategy which takes long position on top decile and short position on bottom decile.

Calendar anomalies examined in this thesis are half-year anomaly and month-of-the-year effect. Portfolio performance evaluation is based on average returns and different risk-adjusted measures represented by the Sharpe ratio and adjusted Sharpe ratio. These measures are compared to the same measures calculated over remainder of the year, buy-and-hold strategy and market returns. Statistical significance of each portfolios' Sharpe ratio with respect to overall market Sharpe ratio is analyzed with Jobson-Korkie z-test (Jobson and Korkie, 1981). This thesis utilizes typographically corrected version of z-test, provided by Memmel (2003). Z-test is used to evaluate the statistical significance of the difference between two portfolios' Sharpe ratios. Z-test value is calculated as in equation (6).

$$Z_{value} = \frac{C_{JK}(\hat{u})}{\sqrt{\hat{\theta}}} = \frac{\sigma_i \mu_j \sigma_j \mu_i}{\sqrt{\hat{\theta}}}$$

with,

$$\theta = \frac{1}{T}[2\sigma_j^2\sigma_i^2 - 2\sigma_j^2\sigma_i^2\sigma_{ji}^2 + \frac{1}{2}\mu_j^2\sigma_i^2 + \frac{1}{2}\mu_i^2\sigma_j^2 - \frac{\mu_j\mu_i}{\sigma_j\sigma_i}\sigma_{ji}]$$

(6)

In Equation (6) μ_i is a mean return of portfolio *i* and *j* respectively, σ_i is a standard deviation of portfolio *i* and *j* respectively, $\hat{\theta}$ is asymptotic variance, *T* number of observations and σ_{ji} covariance of the returns between portfolios *i* and *j*.

Taxes and transaction costs are not taken into consideration; thus, portfolios are assumed to be zero-cost. Important distinction between BAH-strategies and half-year-anomaly strategies is the fact that during the periods of zero investment in strategies trading seasonalities, portfolios are assumed to allocate funds into risk-free instrument of one-month U.S. Treasury bill.

In order to evaluate on whether there are statistically significant seasonalities within anomalies, a dummy regression is employed. Dummy regression is a linear regression with dummy variables for different time periods. Half-year anomaly dummy regression is conducted as my predecessors (e.g., see Bouman and Jacobsen, 2002; Maberly and Pierce, 2004) in order to maintain comparability to earlier results.

$$R_t - Rf_t = \mu_i + \beta_i D_t + \varepsilon_i$$

with,

$$H_0 = \beta_0 = 0$$

(7)

In the dummy regression (7), portfolio excess return over the risk-free instrument $R_t - R_{ft}$. On the other side of the equation μ_i is a constant, which in this instance represents the average return of portfolio i on the period outside calendar anomaly season whereas $\beta_i D_t$ represents the return inside the calendar anomaly season. D_t is a categorial variable or dummy variable, which get value 1 if returns occur inside selected seasonality, otherwise 0 and β_i is a coefficient indicating stock returns of portfolio i. ε_i is error term of the regression with E (ε_i) = 0 and Var (ε_i) = σ^2. Respectively, similar dummy regression is conducted with average return over market yield $R_t - Rm_t$ as a dependent variable (8). By doing this it is possible to examine, whether seasonalities within fundamental anomalies are caused by overall market seasonality effect noticed by Jacobsen *et al.* (2005).

$$R_t - Rm_t = \mu_i + \beta_i D_t + \varepsilon_i$$

with,

$$H_0 = \beta_0 = 0 \tag{8}$$

Month-of-the-year dummy regression is conducted as Marrett and Worthington (2011) and Raj and Thuston (1994) in order to maintain comparability to previous results.

$$R_t - Rf_t = \sum_{i=1}^{n} \beta_i D_t + \varepsilon_t$$

with,

$$H_0 = \beta_i = \beta_{i+n} \, \forall \, n \tag{9}$$

In addition to this, month-of-the-year dummy regression is also conducted with excess return over market yield $R_t - Rm_t$ as a dependent variable but otherwise similarly as in equation (9).

These dummy regressions are conducted on each fundamental anomaly. Form each dummy regression, Student's t-test based probability (*p-value*) values are obtained in order to examine the risk level (*confidence level*) of each regression. Risk level indicates the probability of randomness in results. Risk levels of 1%, 5% and 10% are used throughout this thesis. Furthermore, in order to avoid so-called dummy-variable trap, which occurs in when all dummy variables are included in regression resulting in a perfect multicollinearity, constant term is dropped out in each dummy regression. Due to the leptokurtic distribution often discovered in stock market returns data (Selvarani and Jenefa, 2009) and other violations in regression assumptions concerning residuals (ε_t = i.i.d), throughout the dummy regressions, the Newey-West (1987) adjusted standard errors are used to avoid the problem related to heteroscedasticity and autocorrelation of residuals. Lag-length (m) used in the Newey-West corrected standard errors is defined with respect to conditions introduced by Newey and West (1987).

The lag length grows with respect to the sample size T.

$$\lim_{T \to \infty} T = +\infty$$

The lag length grows at a slower rate than $T^{\frac{1}{4}}$.

$$\lim_{T \to \infty} [m(T)/T^{\frac{1}{4}}] = 0 \tag{10}$$

With respect to these conditions, lag length used in regression can be determined to be integer part of $T^{\frac{1}{4}}$. The Dickey-Fuller test (**Appendix 8**) is conducted in order to test each factor-portfolios' data for unit roots. All data tested were proved to be stationary.

In addition to dummy regressions, Welch's (1947) t-test approach is conducted for detecting differences in returns distribution between half-year anomaly period and remainder of the year. Furthermore, in order enhance robustness of results, liquidity differences between half-year anomaly period (H1) and remainder of the year (H2) is also examined via Welch's t test in a somewhat similar manner as Jacobsen and Visaltanachoti (2009).

$$Welch's\ T\ Stat = \frac{\overline{X_1 - X_2}}{\sqrt{(\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2})}} \tag{11}$$

Where degrees of freedom (ν) and t statistic are used with t-distribution to test the significance level of results. $\overline{X_\iota}$ stands for sample, s_i standard deviation and N_i sample size.

$$(\nu) = \frac{(\frac{s_1^2}{N_1} + \frac{s_2^2}{N_2})^2}{\frac{s_1^4}{N_1^2 \nu_1} + \frac{s_2^4}{N_2^2 \nu_2}}$$

where, $\nu_1 = N_1 - 1$ and $\nu_2 = N_2 - 1$.

(12)

In robustness checks possible factors affecting results are taken into consideration. Multifactor model is employed in order to examine whether seasonalities have significant explanatory power after accounting for other widely known risk factors. Liquidity measure of Pastor and Stambaugh (2003) is used to examine whether significant liquidity differences between periods of H1and H2 have existed. In addition to this, regressions where macroeconomic environment is taken into consideration are conducted in order to enhance the validity of the obtained results. Pragmatic view is also taken by investigating nested anomalies within two separate time periods. First subset contains data from 1963 to 1990 (period 1) and the second from 1991 to 2019 (period 2). Dividing data into two subsets provides thesis with more detailed information about the recent past when economic environment and market conditions have changed dramatically. Furthermore, observing past returns from 1963 to 1990 provides a distinct reference value to other subperiod's returns. The before-mentioned regressions are conducted for each period. Regressors and their statistical significance in explaining the dependent variable is compared between each subset in order to come up with a conclusion of the prediction power of different risk factors and seasonalities within them. This also underlines the usefulness and relevance of different investment strategies in practice.

ARCH model (Engle, 1982) can be treated as an extension to basic linear regression model that allows the conditional variance of the error term change over time. ARCH model allows the conditional variance to be dependent on past errors whereas generalized ARCH (GARCH) model takes also past variance into consideration. Generalized autoregressive conditional heteroscedasticity model GACRH (*q, p*) (Bollerslev, 1986) is employed in order to examine the possible half-year anomaly and time varying volatility within factor-portfolios. GARCH model uses maximum likelihood method to discover the most likely values of parameters given the actual data. GARCH model is employed similarly to Stenius

(1991) and Lean (2011), for example, by allowing conditional variance to enter into original conditional mean-equation.

5. RESULTS

In the next section, I will empirically examine whether seasonalities exist among anomalies in the U.S. markets. Firstly, absolute returns of different anomalies and strategies trading seasonalities within them are examined. In addition to this, risk-adjusted measures for these strategies are presented in order to evaluate the risk related to these strategies. Secondly, statistical significance of the results is examined in order to come up with a conclusion on whether there is significant seasonalities within anomalies and would it be possible for a rational margin investor to capitalize these strategies.

5.1. Fundamental anomalies

Figure 1 demonstrates the cumulative returns of strategies trading anomalies which are in this thesis named as buy-and-hold strategies (BAH). When it comes to cumulative returns without any risk adjustment or other considerations, momentum and value portfolios are the best performing investment strategies on a long run in U.S. stock market. To be more specific, decile portfolios based on price momentum and multiples BE/ME, E/P and CF/P are superior compared to other portfolios in terms of absolute returns.

Table 2 represents the returns and risk adjustments for long strategy on BAH portfolios based on different firm-specific factors. From these metrics we can also conclude, that momentum and value investing have been superior strategies between 1963 and 2019. Portfolio based on company's BE/ME has geometric annual mean return of 13.34% whereas MOM portfolio astonishing 16.69%. When considering solely mean returns, the best performing value portfolio is the one based on company's E/P. This portfolio yielded 13.93% annually. In addition to this, E/P portfolio has the third highest Sharpe ratio and adjusted Sharpe ratio. When taking risk into account with Sharpe ratios, MOM and BETA portfolios have marginally outperformed others.

One mentionable trait in the success of the MOM portfolio is the short investing period inside market cycles. Monthly rebalancing of the MOM portfolio creates superior returns and risk adjusted returns with respect to other portfolios. During the rotation between value stocks and glamour stocks and when investor sentiment is relatively high, momentum investing can be considered as noteworthy strategy alongside with value-investing as was found by Lee and Song (2003). **Figure 1** demonstrates the post-financial crisis success of momentum investing as “winner takes it all” principle has become more relevant in the U.S stock markets. Although MOM portfolio with buy-and-hold principle has generated comprehensively better absolute returns with respect to other factor portfolios during the investigation period, accumulation of the superior performance has occurred in the most recent decade.

When comparing mean returns of long portfolios based on anomalies, they all have systematically beaten market returns. The time period from 1963 to 2019 has been especially profitable for momentum and value investing. However, portfolios based on company size and level of accruals have also proven to be possible strategies to beat the market. Portfolios’ mean returns indicate, that a simple investing strategy taking long position according to the firm specific factor can outperform the U.S. stock market index on a long run.

Z-values in **Table 2** indicate that long only portfolios based on price momentum, E/P, CF/P and company beta have significantly better Sharpe ratios than the market portfolio. Consistent with the results of O'Shaughnessy (2005, 76,131), E/P portfolio has generated statistically significant risk-adjusted returns compared to market portfolio with a confidence level of 95%. MOM portfolio’s risk-adjusted returns have also been statistically significant. Moreover, MOM portfolio is the only portfolio that has statistically significant z-value at the 99% confidence level. According to z-values, the best performing portfolio on a risk-adjusted basis during the period between 1963 and 2019 has been MOM portfolio.

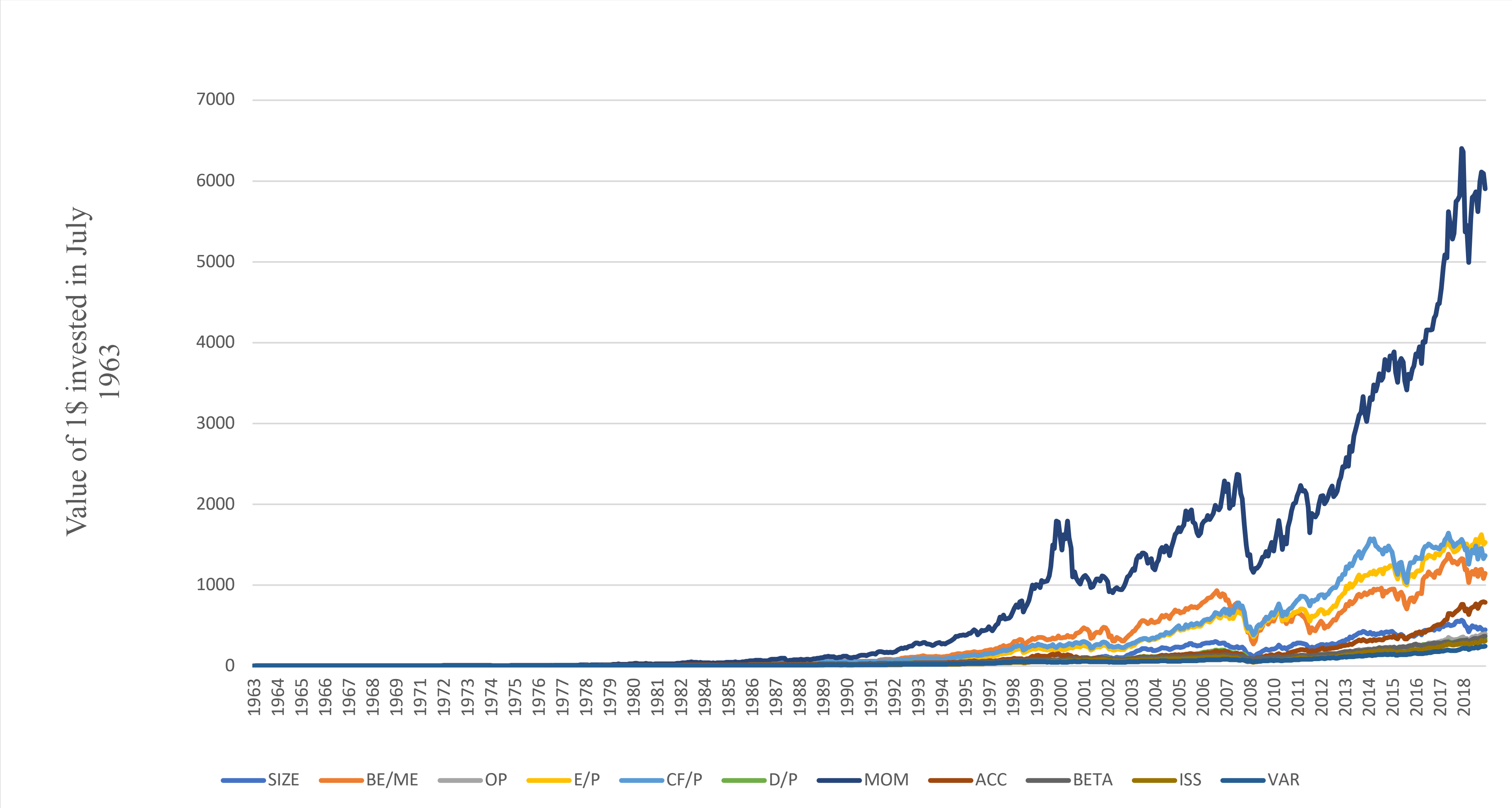


Figure 1. **Cumulative returns of long-only top decile portfolios between 1963 and 2019**.

Figure shows the value of 1$ invested in each decile portfolio from 1963 to 2019. Portfolios are value-weighted. Portfolios include all U.S. securities listed on Nasdaq, NYSE and Amex. Limits of deciles are based on NYSE breakpoints. Market portfolio is the overall market return during the investigation period from July 1963 to September of 2019.

Table 2. Returns of BAH long-only top decile portfolios and risk-adjusted metrics.

Returns in this table are returns of zero-cost long strategy, which is calculated as returns of top or bottom decile for each individual factor, according to firm-specific characteristic. Returns and volatility measures are annualized and consist of Amex, NYSE and Nasdaq securities returns data from 1963 to 2019. Returns are annualized geometric mean returns for each portfolio. 1-month U.S. treasury bill acts as a risk-free rate. Figures in this table are percentages excluding beta, SR and ASR. Z-value is calculated with respect to market portfolio. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

LONG	**Geometric**	**Volatility**	**Beta**	**SR**	**ASR**	**Z (vs Rm)**
Market	10,21	15,17				
SIZE	11,46	21,61	1,1047	0,4009	0,3984	0,1984
BE/ME	13,34	21,1	1,1439	0,4862	0,4758	0,845
OP	11,24	15,72	0,969	0,4683	0,4558	1,032
E/P	13,93	18,02	1,0205	0,5639	0,5516	**2,0358****
CF/P	13,69	18,08	1,005	0,5516	0,5382	1,7688*
D/P	10,91	15,27	0,6509	0,4597	0,4284	0,3647
MOM	16,69	21,11	1,1776	0,6256	0,6105	**2,772*****
ACC	12,59	19,37	1,1619	0,4758	0,4685	1,0072
BETA	11,08	11,82	0,6119	0,5667	0,5591	1,6863*
ISS	10,76	15,06	0,8971	0,4529	0,4406	0,5834
VAR	10,28	11,29	0,5856	0,5227	0,5197	1,1901

When considering long-short factor portfolios within fundamental anomalies, portfolios' returns have systematically underperformed compared to market returns with the exception of MOM portfolio. (**Table 3**). Predominantly, long position and short selling according to each anomaly has not been successful investing strategy, in terms of absolute returns. The worst performing long-short factor portfolio has been BETA portfolio with negative geometric mean returns of –3.11%. In addition to this, long-short BETA strategy has had a substantial volatility of 22.56% compared to a similar long BETA strategy (11.82%). Z-values underline to poor performance of long-short factor portfolios with respect to market portfolio. Portfolios based on company size, value and beta have statistically significant difference in Sharpe ratio compared to market Sharpe. In other words, these portfolios have significantly underperformed on a risk-adjusted basis compared to market performance. On the other hand, long-short MOM strategy has performed soundly with annualized geometric mean return of 12.77%. However, long-short MOM portfolio has substantially higher volatility compared to market volatility, thus on a risk adjusted basis, the performance of MOM portfolio has not been superior with respect to U.S. overall market performance. Nevertheless, long-short MOM factor portfolio has been the best performing portfolio out of all selected long-short portfolios with absolute returns and Sharpe ratios. There is also a noteworthy distinction between long-short MOM SR (0.4432) and ASR (0.3819) indicating a rather strong negative skewness of returns, which is not favorable for investor.

Table 3. Returns of BAH long-short factor portfolios and risk-adjusted metrics.

Returns in this table are returns of long-minus-short strategy, which is calculated as returns of top decile minus returns of the bottom decile for each individual factor, according to firm-specific characteristic. Returns and volatility measures are annualized and consist of Amex, NYSE and Nasdaq securities returns data from 1963 to 2019. Returns are annualized geometric mean returns for each portfolio. 1-month U.S. treasury bill is used as a risk-free rate. Figures in this table are percentages excluding beta, SR and ASR. Z-value is calculated with respect to market portfolio. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

LONG-SHORT	**Geometric**	**Volatility**	**Beta**	**SR**	**ASR**	**Z (vs Rm)**
SIZE	1,67	16,37	0,176	-0,0026	-0,0026	**2,9928*****
BE/ME	3,31	16,28	0,0828	0,0006	0,0006	**2,3066****
OP	2,16	13,86	-0,3493	-0,002	-0,002	**2,3649****
E/P	3,07	14,64	-0,1381	-0,0007	-0,0007	**2,2319****
CF/P	3,15	14,6	-0,1468	-0,0006	-0,0006	**2,1979****
D/P	-0,8	18	-0,5357	-0,0067	-0,0067	**2,7555*****
MOM	12,77	24,06	-0,26814	0,4432	0,3819	0,1205
ACC	5,25	9,61	-0,0668	0,1064	0,1074	1,5795
BETA	-3,11	22,56	-0,9997	-0,0116	-0,0116	**2,6485*****
ISS	4,74	11,12	-0,2825	0,0622	0,0624	1,6102
VAR	2,24	26,8	-1,0701	0,0506	0,0505	1,5384

5.2. Nested Anomalies

5.2.1. Half-year Effect

Many researchers have found, that stock returns are not evenly distributed throughout the year. Moreover, during the half-year period from November to April, stock returns have a tendency of being superior compared to other half-year period from May to October.(e.g., see Jacobsen and Bouman, 1997; Andrade *et al*., 2013; Zarour, 2004) Like many earlier studies before, the research results of this thesis also point out the existence of half-year anomaly. In this section half-year anomaly is referred as H1 whereas other half of the year is referred as H2. When we compare results of long H1 to H2, there is a significant difference in terms of absolute returns. (**Table 4** and **Table 5**)

Table 4. Returns and risk-adjusted metrics of half-year strategy (H1) within each anomaly.

Returns in this table are returns of long and long-minus-short strategy, which is calculated as returns of top minus returns of bottom decile for each individual factor, according to each anomaly. Returns, volatility and risk measures are annualized and consist of Amex, NYSE and Nasdaq securities returns data from 1963 to 2019. 1-month U.S. treasury bill acts as risk-free rate. In H1-strategy, portfolios are fully allocated into equities between November and April each year whereas time period between May and October funds are invested in risk-free instrument. Market returns are also half-year figures analogously to those for anomaly portfolios, thus half of the year consist of risk-free rate. Figures in this table are percentages excluding Beta, SR and ASR. Z-value is calculated with respect to market portfolio. Z-value is calculated solely based on half-year returns on a yearly basis for each factor portfolio and market portfolio, thus risk-free rate of return during out-of-the-market periods is excluded in calculations. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

H1 LONG	**Geometric**	**Volatility**	**Beta**	**SR**	**ASR**	**Z (vs Rm)**
SIZE	14,39	15,63	0,503	0,936	0,887	0,7366
BE/ME	15,99	15,28	0,531	1,091	0,819	**2,0249****
OP	10,5	10,92	0,447	0,8	0,817	0,4011
E/P	14,24	12,62	0,468	1,105	1,084	**2,4628****
CF/P	14,27	12,74	0,463	1,097	1,029	**2,2861****
D/P	8,85	11,47	0,314	0,575	0,4	1,5109
MOM	14,42	14,66	0,524	0,9913	0,98	1,3298
ACC	12,55	13,6	0,542	0,87	0,837	0,474
BETA	8,97	7,82	0,251	0,805	0,798	0,1724
ISS	10,62	10,31	0,401	0,851	0,84	0,2301
VAR	8,72	7,84	0,255	0,759	0,765	0,5014
MARKET	10,41	10,22	0,45			

LONG-SHORT	Geometric	Volatility	Beta	SR	ASR	Z (vs Rm)
SIZE	7,11	12,64	0,077	0,348	0,352	1,9211*
BE/ME	8,57	12,46	0,046	0,51	0,538	1,2317
OP	0,49	10,21	-0,146	-0,01	-0,01	**4,3069*** **
E/P	6	10,79	-0,05	0,245	0,248	**2,0651*** **
CF/P	6,16	10,81	-0,051	0,264	0,269	**2,0011** **
D/P	-0,7	13,04	-0,215	-0,016	-0,016	**4,1748*** **
MOM	5,75	18,89	-0,1601	0,2279	0,2109	**2,0429** **
ACC	4,06	6,92	-0,007	-0,001	-0,001	**3,3201*** **
BETA	-4,07	16,32	-0,488	-0,034	-0,034	**4,2268*** **
ISS	4,21	8,06	-0,13	0	0	**2,7062*** **
VAR	-1,83	20,57	-0,542	-0,024	-0,024	**3,2991*** **

The difference between returns on H1 and H2 is substantial. Despite the superior performance, volatility levels of H1 compared to H2 are only slightly higher, approximately by 1.24 percentage points on average. Furthermore, performance metrics SR and ASR are systematically higher for H1 portfolios compared to H2. This indicates that higher mean returns in H1 are not just compensation of increased risk compared to H2. Visual representation of H1 and H2 long portfolios in **Appendix 9** and **Appendix 10**.

H1 long-only value portfolios have outperformed others in terms of mean returns and Sharpe ratios. However, they are portfolios with higher annual volatility and therefore, returns can at least partially be associated with higher risk. Also, decile portfolio of SIZE has performed well, although being the most volatile portfolio between 1963 – 2019. In addition to this, H1 MOM portfolio has performed soundly in terms of geometric mean returns. When looking at annualized geometric mean returns, H1 long portfolios of D/P, BETA and VAR portfolios have underperformed compared to the market portfolio. H1 long-short factor portfolios have systematically been beaten by market portfolio.

H1 long portfolios' z-values in **Table 4** underline that value portfolios (BE/ME, E/P and CF/P) have performed significantly better than the market portfolio on a risk-adjusted basis. Statistical significance of these results holds at the 5% risk level. Therefore, we can conclude that there appears to be statistically significant half-year anomaly on a risk-adjusted basis in these portfolios, based on z-values. Majority of H1 long-short factor portfolios have statistically significant z-values indicating that they have underperformed on a risk-adjusted basis with respect to market portfolio. Furthermore, long-short factor portfolios in H1 and H2 have systematically underperformed to long portfolios of the same fundamental anomaly. (**Table 4 and Table 5)** However, long-short H2 MOM portfolio has generated statistically significant risk-adjusted returns with respect to market performance at the 5% risk level. This indicates that during H2 period, short-selling loser stocks and buying winner stocks has been a robust investing strategy during the sample period.

Table 5. Returns of zero-cost half-year strategy (H2) within each anomaly.

Returns in this table are returns of long and long-minus-short strategy, which is calculated as returns of top minus returns of bottom decile for each individual factor, according to each anomaly. Returns and volatility measures are annualized and consist of Amex, NYSE and Nasdaq securities returns data from 1963 to 2019. Returns are annualized geometric mean returns for each portfolio. 1-month U.S. treasury bill is used as risk-free rate of return. In H2 -strategy, portfolios are fully allocated into equities between May and October each year whereas time period between November and April funds are allocated in risk-free instrument. Market returns are also half-year figures with same decree as portfolios trading anomalies. Figures in the table are percentages excluding Beta, SR and ASR. Z-value is calculated with respect to market portfolio. Z-value is calculated solely based on half-year returns on a yearly basis for each factor portfolio and market portfolio, thus risk-free rate of return during out-of-the-market periods is excluded in calculations. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

H2 LONG	**Geometric**	**Volatility**	**Beta**	**SR**	**ASR**	**Z (vs Rm)**
SIZE	1,97	14,87	0,6005	-0,006	-0,006	1,7644*
BE/ME	2,26	14,49	0,612	-0,005	-0,005	1,7926*
OP	5,3	11,4	0,5208	0,159	0,156	1,5715
E/P	4,35	12,94	0,5517	0,063	0,062	0,0519
CF/P	4,12	12,87	0,5405	0,037	0,037	0,2121
D/P	6,63	10,22	0,3359	0,333	0,33	1,8431*
MOM	6,72	15,38	0,6523	0,291	0,283	**2,558****
ACC	4,68	13,87	0,6185	0,102	0,101	0,5728
BETA	6,67	9,01	0,3599	0,367	0,361	**2,8320*****
ISS	4,77	11,06	0,4949	0,094	0,093	0,4825
VAR	6,15	8,25	0,3293	0,304	0,298	**2,2439****
MARKET	4,46	11,27	0,5489			

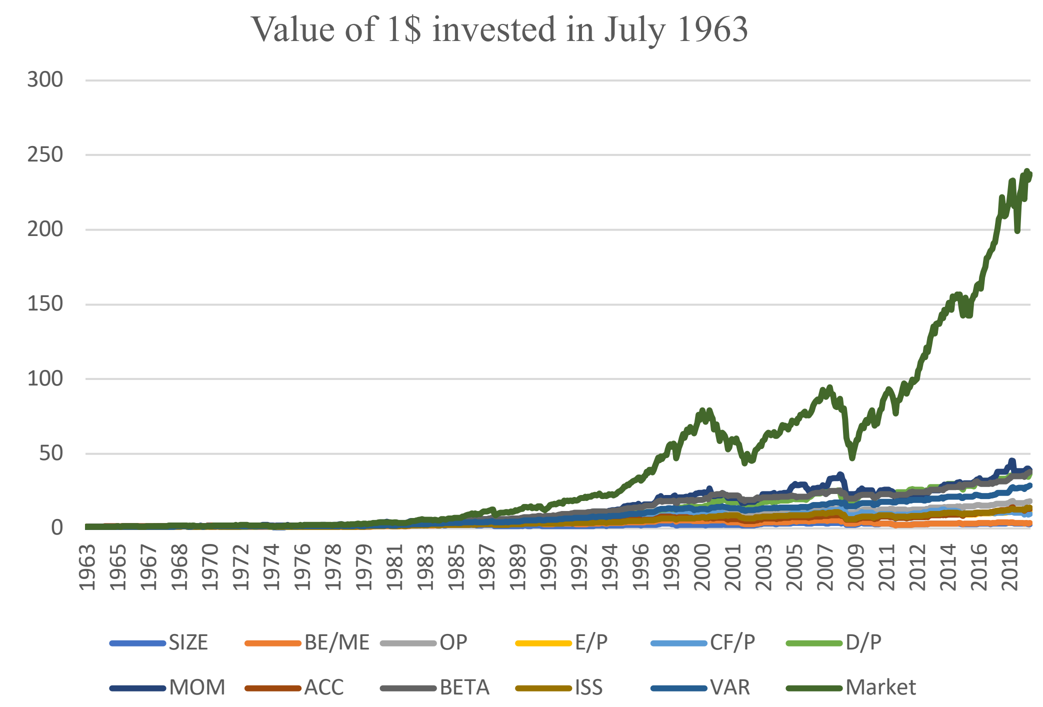
LONG-SHORT	**Geometric**	**Volatility**	**Beta**	**SR**	**ASR**	**Z (vs Rm)**
SIZE	-0,67	10,34	0,0979	-0,014	-0,0136	**2,9038*****
BE/ME	-0,43	10,36	0,0353	-0,013	-0,0128	**2,5831*****

OP	6,39	9,36	-0,2046	0,316	0,3223	0,8102
E/P	1,75	9,9	-0,0894	-0,006	-0,0064	1,3466
CF/P	1,69	9,82	-0,0972	-0,007	-0,0065	1,3824
D/P	4,54	12,42	-0,3222	0,075	0,075	0,0502
MOM	11,6	15,06	-0,1093	0,722	0,6852	**2,319****
ACC	5,84	6,73	-0,0614	0,284	0,2903	0,7867
BETA	5,68	15,51	-0,5126	0,2	0,2003	0,4116
ISS	5,17	7,71	-0,1538	0,145	0,1451	0,276
VAR	8,98	17,08	-0,5297	0,461	0,46	1,188

During H2 period, long-only top decile portfolios formed on BETA, VAR and MOM have generated superior risk-adjusted returns compared to the market portfolio. Among these three, the one based on beta has outperformed market portfolio in terms of risk-adjusted returns at the 1% risk level, whereas VAR and MOM top decile portfolios have done that at risk level of 5%. These results underline the existence of low volatility anomaly in long portfolios during the period of H2 and are consistent with results of Blitz and Vliet (2007). However, results of this thesis prove that low volatility anomaly is statistically more significant with respect to market portfolio in terms of risk-adjusted returns in the period of H2 than based on buy-and-hold principle.

Every investor’s and fund manager’s ultimate goal in stock picking is to beat the selected benchmark index. Therefore, it is intriguing to compare buy-and-hold principle market returns and H1 returns with risk free instrument. Annualized geometric mean market return for time period from 1963 to 2019 is 10.21% and volatility 15.17% (**Table 2**). Moreover, H1 geometric mean market return is 10.41% and volatility 10.22%, thus lower volatility and higher mean return (**Table 4**). H1 factor portfolios, excluding VAR, BETA and D/P portfolios, have outperformed mean market return in H1 period. Furthermore, only MOM, BE/ME and SIZE portfolios have higher annual volatility than overall U.S market index (14.66%, 15.28% and 15.63%), whereas other portfolios have lower levels of volatility with respect to market volatility. However, risk-free instrument during out-of-the-market periods in half-year strategies have a substantial impact on volatility levels. Furthermore, results of this thesis indicate that Adjusted Sharpe ratio offers marginal improvement to traditional Sharpe ratio, as many of my predecessors have also noticed. (e.g., see Eling and Schuhmacher, 2006; Pätäri and Tolvanen, 2009; Pezier and White, 2006)

Panel A: H2 portfolios cumulative returns



Panel B: H1 portfolios cumulative returns

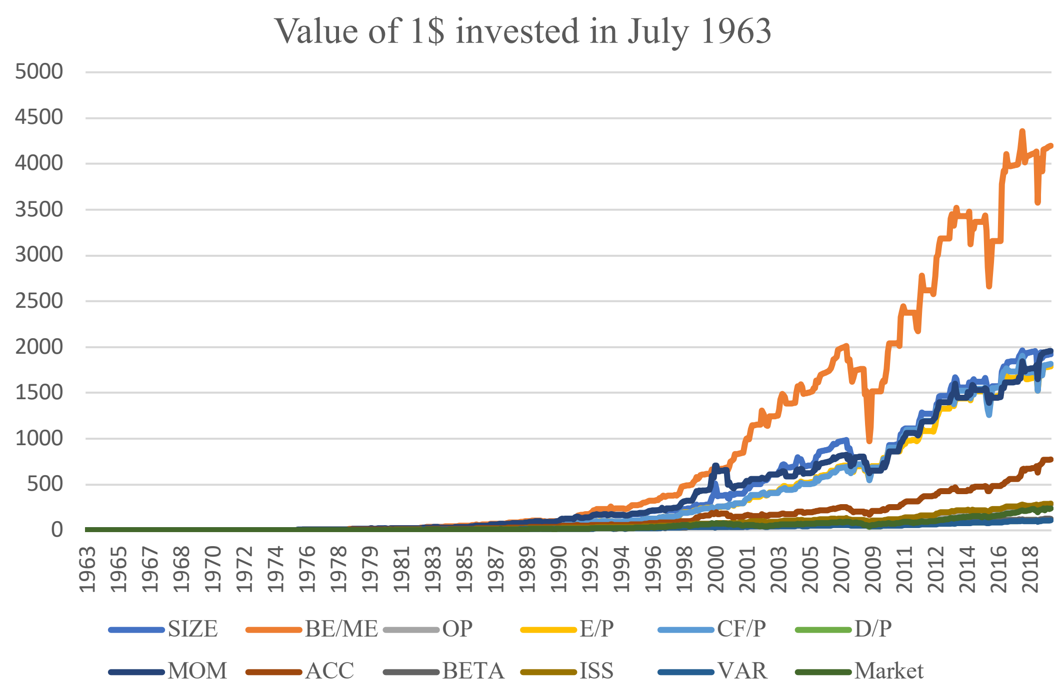


Figure 2. Cumulative returns of long-only top decile portfolios within half-year anomaly and rest of the year.

Table includes yearly time periods of H1 (Panel B) and H2 (Panel A). Figure shows the value of 1$ in each decile portfolio from 1963 to 2019. Portfolios include all U.S. securities listed on Nasdaq, NYSE and Amex. Limits of deciles are based on NYSE breakpoints. Risk-free rate of 1-month U.S. treasury bill is used during out-of-the-market periods in factor portfolios. Market portfolio is overall (BAH) market return of Nasdaq, NYSE and Amex during the investigation period from July 1963 to September 2019.

Figure 2 shows the cumulative returns of H1 and H2 long portfolios from July 1963 to September 2019 and cumulative market return on the same period. Panel B visualizes the superior performance of BE/ME portfolio during H1 and especially during the most recent decades.

Table 6. Annualized returns of nested anomaly strategies.

H1(rf) and H2(rf) use 1-month U.S. treasury bill during out-of-the-market periods. H1 and H2 are annualized returns without risk-free instrument during out-of-the-market periods. Data used in portfolios is monthly returns data of NYSE, Amex and Nasdaq stocks from 1963 to 2019.

LONG	**H1(rf)**	**H1**	**H(rf)**	**H2**
SIZE	14,39	11,84	1,97	-0,29
BE/ME	15,99	13,41	2,26	0,00
OP	10,5	8,06	5,3	2,99
E/P	14,24	11,70	4,35	2,06
CF/P	14,27	11,72	4,12	1,82
D/P	8,85	6,39	6,63	4,29
MOM	14,42	11,87	6,72	4,38
ACC	12,55	10,03	4,68	2,37
BETA	8,97	6,52	6,67	4,33
ISS	10,62	8,14	4,77	2,47
VAR	8,72	6,27	6,15	3,82
Market	10,41	7,93	4,46	2,16

Table 6 shows the annualized returns of H1 and H2 strategies trading anomalies within U.S. stock market. Especially conspicuous distinction between buy-and-hold strategy and half-year anomaly is BE/ME portfolio. Should have investor only bought value stocks based on single fundament of BE/ME and on a yearly basis rebalanced his/her portfolio, cumulative return would have been 114 437% or in annual terms 13.34%. However, if investor would have stayed in the stock markets from November to April each year and during out-of-the-market period re-allocated assets into risk-free instrument, he/she would have obtained astonishing cumulative returns of 419 421% or in annual terms 15.99%. SIZE portfolio has

also performed better with semi-annual holding periods compared to buy-and-hold principle when including risk-free rate of return during out-of-the-market periods. This can be partly stemming from January effect of small cap stocks (e.g., see Keim, 1985; Rozeff and Kinney, 1976).

There is a substantial difference between returns of H1 and H2 when excluding risk-free instrument during out-of-the-market periods. All factor portfolios have generated remarkably higher annualized returns in H1 with respect to H2. **Table 6** shows that the most substantial difference between H1 and H2 returns is in portfolios of SIZE and BE/ME. Amongst value anomaly D/P portfolio has performed the worst in terms of cumulative returns. Poor performance of high dividend paying stocks can be related to the notation that dividend paid out of the company has usually taxation effect which lowers the capital for re-allocation. Another possible reason could be the fact that dividend paid out are also excluded from company’s investments for future profitability and growth. Thus, company could decide to pay dividends rather than exploit investment opportunities with positive net present value. This is often the case because of the investor’s affection to known yield and desire for consumption of dividends received. Dividends also have a signaling effect on company’s performance. Many companies have the image of a stable dividend payer and therefore, there is no incentive for a company to cut dividends and re-allocate capital for future prosperity instead.

There is also a noteworthy divergence between market portfolio return during different time periods. Cumulative market portfolio return during H1with risk free instrument has been 26 124%, thus better than buy-and-hold market portfolio return whereas market return during H2 with risk free instrument has been prudent 1064.8%. Without risk free rate of return H1 market return of 7068% is substantially higher than H2 return of 231.20%. Hence, half-year anomaly appears on a market level as well. These findings are in line with Jacobsen and Bouman (2002) research.

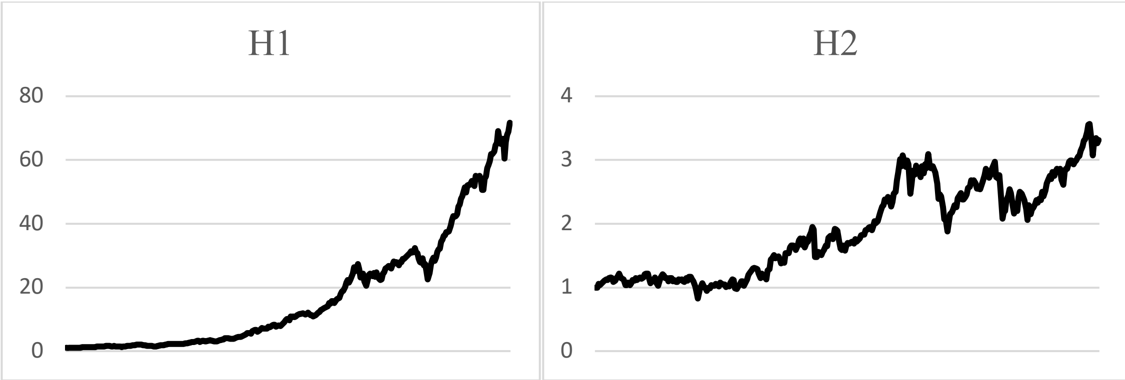


Figure 3. Market yield during period H1 and H2

This figure represents 1$ invested in U.S. market index consisting Amex, NYSE and Nasdaq securities during periods of H1 and H2 between 1963 and 2019. Figures do not include risk-free rate during out-of-the-market periods

In order to emphasize the magnitude of market-wide half-year anomaly, **Figure 3** demonstrates the development of 1$ invested semiannually. 1$ invested in securities between November and April each year has ultimately resulted in more than 71,7$ whereas between May and October each year has resulted in approximately 3,3$. Important distinction in this figure is the exclusion of risk-free rate of return during out-of-the-market periods. H1 has rapid growth and accumulation throughout the time-series whereas H2 appears to have four different stages: firstly stagnation, secondly modest growth, thirdly stagnation and ultimately modest growth.

5.2.1.1. Regression results

Table 7 shows regression estimates for long-only portfolios and t-test based p-values. Coefficients represent monthly returns' figures of each anomaly. Period H1 coefficients for regressions concerning portfolios' excess return over the risk free instrument (H1-Rf) are statistically significant at a 1% risk level within all factor portfolios. This indicates that the time-period of H1 as explanatory dummy-variable is highly significant in explaining excess returns over risk free instrument within anomalies. H1-Rf coefficients significantly differ from zero, thus we can reject the before-mentioned half-year regression null hypotheses.

Furthermore, H2-Rf BETA portfolio returns has statistically significant explanatory power over excess returns with confidence level of 95%.

H1-Rf coefficients indicate that half-year anomaly is the most significant within BE/ME portfolio, although almost equally significant results were obtained by SIZE portfolio. On the other hand, during H2 period the average monthly return over the risk-free instrument have been negative within both of these portfolios. This offers us a captivating evidence of the half-year anomaly within fundamental anomalies. Furthermore, rest of the portfolios have somewhat similar results. **Table 7** also provides us with a benchmark of market portfolio monthly excess return over the risk-free instrument. The values of adjusted R-squared in regressions with excess return over risk-free rate as dependent variable are modest, as can be expected, when using solely time-period based dummy variables as explanatory variable. Value portfolios of E/P, CF/P and BE/ME have obtained higher coefficients than other portfolios and therefore, indicating stronger half-year effect within value anomaly. Moreover, there appears to be strong half-year effect in MOM portfolio returns, thus past winner stocks tend to perform better in the future during H1 compared to H2.

In order to measure the magnitude of half-year effect and enhance the reliability of the obtained results, regressions are also conducted as excess return over market yield as the dependent variable (*H1-Mrkt & H2-Mrkt*). This way we observe whether seasonalities within fundamental anomalies are stemming from overall market seasonality effect mentioned by Jacobsen *et al.* (2005) or could there be exploitable inefficiencies within the cross section of certain equity returns. From **Table 7** we can see that long-only portfolios of SIZE, BE/ME, E/P, CF/P, MOM and ACC have significantly outperformed the market portfolio at the risk level of 1% during H1. BE/ME portfolio has generated monthly excess return of 0.9% over the market during the investigation period ($p<0.01$). Moreover, market seasonality effect absorbs explanatory power of half-year effect completely from the rest of the portfolios. However, during H2 period MOM and BETA portfolios have significantly outperformed market portfolio. Performance of long-only H2 BETA portfolio is especially intriguing due to the substantial difference in portfolio returns with respect to market portfolio between H1 and H2. Based on these results, we can conclude that overall market seasonality effect does not account for returns generated by long portfolios based on value, size, momentum and accruals anomaly. Moreover betting against beta present itself as a noteworthy strategy during H2 period.

Table 7 Regression results of H1 and H2 within each long-only top decile portfolio.

The dependent variable in each regression is the excess return over the risk-free rate of each factor portfolio whereas the independent variable is dummy variable of time periods H1 and H2. P-value of each regression in parenthesis. Each regression contains 675 observations. Regressions use Newey-West HAC (heteroscedasticity and autocorrelation) corrected standard errors. Lag length used in Newey-West error terms is m=3 and calculated according to Newey and West (1987). Adjusted R-Squared is based on regression with H1-Rf and H2-Rf. Statistically significant values are bolded and marked with asterisks. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

LONG	**Mrkt-Rf**	**BAH**	**H1-Mrkt**	**H2-Mrkt**	**H1-Rf**	**H2-Rf**	**Adj. R-Squared**
SIZE	0,53 %	0,72 %	**0.007***** (0.004)	-0.003	**0.017***** (0.000)	-0.002	3,41 %
BE/ME		0,86 %	**0.009***** (0.000)	-0.0028	**0.019***** (0.000)	-0.002	4,63 %
OP		0,62 %	0.0003	0.0014	**0.010***** (0.000)	0.002	2,28 %
E/P		0,85 %	**0.0062***** (0.000)	0.0002	**0.016***** (0.000)	0.001	4,35 %
CF/P		0,83 %	**0.006***** (0.000)	-0.0002	**0.016***** (0.000)	0.001	4,36 %
D/P		0,59 %	-0.002	0.003* (0.065)	**0.008***** (0.004)	0.004* (0.086)	1,62 %
MOM		1,10 %	**0.007***** (0.000)	**0.0045***** (0.007)	**0.016***** (0.000)	0.005	3,75 %
ACC		0,77 %	**0.004***** (0.006)	0.0009	**0.014***** (0.000)	0.002	2,71 %
BETA		0,56 %	-0.0025* (0.091)	**0.0031**** (0.029)	**0.007***** (0.000)	**0.004**** (0.042)	2,57 %
ISS		0,57 %	0.0003	0.0004	**0.010***** (0.000)	0.001	2,44 %
VAR		0,49 %	-0.003* (0.056)	0.002	**0.007***** (0.000)	0.003	2,30 %

Table 8 describes the regression results of long-short portfolio for H1 and H2 periods. From this table we can see that regressions utilizing excess return over the risk free instrument tend to have significant negative coefficients for H1 and H2 indicating that long-short portfolios have usually performed rather poorly. However, VAR portfolio has generated

statistically significant returns during H2 at the 5% risk level and moreover MOM portfolio has statistically significant H2 coefficient at the risk level of 1% indicating that MOM portfolio have been statistically the best performing long-short factor portfolio during H2. Moreover, when observing excess return over market index, long-short MOM portfolio has significantly outperformed market portfolio during H2 at 99% confidence level with monthly excess return of 1.18%. After adjusting regressions with market seasonality effect, half year effect completely disappears from other long-short factor portfolios.

Interestingly, long and long-short regression results seem to be especially contradictory with Gezelius (2020) arguments about the validity of P/B metric in describing the company's future expected returns and valuation. Furthermore, BE/ME seems to be exclusively better predictor of future returns than operating profitability, inconsistent with findings of Novy-Marx (2013), hence regression results in **Table 7** suggest that for BE/ME portfolio so-called *Sell in May and go away* principle appears to be more beneficial compared to other portfolios. Success of BE/ME portfolio in H1 period indicates that by selecting companies with high levels of BE/ME in year t-1, remarkably sound outcome can be achieved in terms of returns in H1 period.

Table 8. Regression results of H1 and H2 within each long-short factor portfolio.

The dependent variable in each regression is the excess return over the risk-free rate of each factor portfolio whereas the independent variable is dummy variable of time periods H1 and H2. Each regression contains 675 observations. P-value of each regression in parenthesis. Regressions use Newey-West HAC corrected standard errors. Lag length used in Newey-West error terms is m=3 and calculated according to Newey and West (1987). Adjusted R-Squared is based on H1-Rf and H2-Rf regression. Statistically significant values are bolded and marked with asterisks. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

LONG-SHORT	**M-Rf**	**BAH**	**H1-Mrkt**	**H2-Mrkt**	**H1-Rf**	**H2-Rf**	**Adj. R-Squared**
SIZE	0,53 %	-0,13 %	-0.0047	**-0.0085*****	0.005*	-0.002	1,65 %
				(0.003)	(0.076)	(0.004)	
BE/ME		0,00 %	-0.002	**-0.008****	**0.007****	**-0.007*****	2,20 %
				(0.011)	(0.012)	(0.003)	
OP		-0,12 %	**-0.016*****	0.0027	**-0.006****	0.003	1,17 %
			(0.000)		(0.014)		
E/P		-0,04 %	-0.006*	-0.004	0.003	-0.004*	0,39 %
			(0.066)			(0.070)	
CF/P		-0,03 %	-0.006*	-0.0047	0.003	-0.004*	0,47 %

		(0.082)			(0.062)	
D/P	-0,31 %	**-0.017*** **	0.0003	**-0.007** **	0.001	0,72 %
		(0.000)		(0.013)		
MOM	0,89 %	-0.0048	**0.0118*** **	0.005	**0.013*** **	1,60 %
			(0.008)		(0.000)	
ACC	0,09 %	**-0.0104*** **	0.0015	-0.001	0.002	0,05 %
		(0.000)				
BETA	-0,43 %	**-0.022*** **	0.003	**-0.012*** **	0.004	1,63 %
		(0.000)		(0.001)		
ISS	0,06 %	**-0.01*** **	0.0005	-0.000	0.001	-0,21 %
		(0.005)				
VAR	0,11 %	**-0.017*** **	0.008	-0.007	**0.009** **	0,83 %
		(0.008)			(0.014)	

Welch's t-test is used to evaluate the statistical significance of the difference between returns of period H1 and H2. Welch's t-test does not assume the equal variance or sample size and therefore when considering financial data can be considered more robust in explaining difference between two samples than traditional Student's t-test. Panel A of **Table 9** provides a strong evidence of half-year anomaly within certain long portfolios. According to Welch's t-test, half-year anomaly occurs especially for long-only top decile portfolios of SIZE, BE/ME, E/P and CF/P, which all have statistically significant t-stats at the 99% confidence level. Moreover, portfolio based on operating profitability and stock's price momentum tend to generate significantly better outcomes during H1 than H2. Interestingly also portfolios formed on accruals and net share issuances exhibit statistically significant difference between mean returns of H1 and H2 at the 99% confidence level. Furthermore, Welch's t test indicates, that there is no significant difference between returns of H1 and H2 in high dividend yield portfolio, which is consistent with results of Jacobsen *et al*. (2005).

Panel B in **Table 9** represents long-short factor portfolios. Long-short factor portfolios have almost systematically achieved statistically significant results. Intriguing finding is the fact that portfolios of OP, D/P, BETA and VAR have performed better during the H2 period and moreover all long-short factor portfolios, excluding ACC and ISS, have statistically significant difference in mean returns between H1 and H2 at a risk level of 1% and 5%. Based on these results we can conclude that value stocks and stocks based on their market capitalization tend to exhibit strongest half-year anomaly and moreover nested anomaly strategies based on these investing principles and half-year holding period have a tendency of generating superior outcomes in the long run.

Table 9. Mean returns between H1 and H2 within long-only (long-short) portfolios and Welch's t-statistic.

Figure in H1 row is half-year anomaly period mean return for each factor portfolio whereas H2 is rest of the year mean return for each factor portfolio. Panel A represents strategy, that takes long position of securities and Panel B describes long-short strategy. **ν** represents the degrees of freedom in Welch's t-test and *Tstat* is the obtained t-statistic from Welch's t-test. Newey-West HAC corrected standard errors are used throughout the Welch's test. Lag length used in Newey-West error terms is m=3 and calculated according to Newey and West (1987). Statistically significant values are bolded and marked with asterisks when considered important. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

Panel A	SIZE	BE/ME	OP	EP	CF/P	D/P	MOM	ACC	BETA	ISS	VAR
H1	1,012	1,013	1,009	1,012	1,012	1,008	1,012	1,011	1,007	1,009	1,007
H2	1,003	1,003	1,005	1,004	1,004	1,006	1,006	1,005	1,006	1,004	1,005
ν	1345	1344	1346	1347	1348	1330	1345	1347	1322	1341	1345
Tstat	**4,0378*** **	**4,528*** **	**2,288** **	**3,747*** **	**3,855*** **	1,082	**2,428** **	**2,794*** **	1,284	**2,663*** **	1,557

Panel B	SIZE	BE/ME	OP	EP	CF/P	D/P	MOM	ACC	BETA	ISS	VAR
H1	1,006	1,008	1,001	1,005	1,005	1	1,006	1,004	0,998	1,004	1
H2	1	1	1,006	1,002	1,002	1,004	1,01	1,005	1,006	1,004	1,008
ν	1297	1305	1338	1338	1336	1345	1284	1347	1345	1345	1304
Tstat	**3,579*** **	**4,116*** **	**-3,045*** **	**2,142** **	**2,261** **	**-2,099** **	-1,425	-1,307	**-3,165*** **	-0,598	**-2,728*** **

Tax-selling, January effect or even some other superior month could partially account for half-year anomaly. To further investigate seasonalities within factor portfolios, next chapter divides stock market year to even smaller pieces by investigating one month at a time. This way, we can obtain a more holistic view on anomalous returns within calendar year and conclude on whether half-year effect is generally produced by some specific months or does it exist on a boarder scale.

5.2.2. Month-of-the-year

In this section, month-of-the-year effect is evaluated from the point of view of returns and performance indicators. In strategies trading one month-of-the-year, returns are excess returns over the risk-free rate. Moreover, out-of-the-market periods are not accounted in calculations in order to obtain more robust view on each individual month's performance.

During the time period of investigation monthly excess market return over the risk-free instrument has been 0.53%. From **Table 10** we can see that based on excess returns over the risk-free rate, January within SIZE portfolio is ultimately superior combination compared to any other month within other anomalies, resulting in average monthly excess return of 5.28%. Moreover, January have performed well in portfolios of BE/ME, E/P, CF/P with average monthly excess returns being over 2% in each. April and CF/P has also performed notably well with excess return of 2.06% compared to April within other anomalies. Another interesting fact is sound performance of ACC and MOM portfolios during the month of November (1.88% and 2.13%). The worst months within long-only portfolios in terms of excess returns have been September with composite monthly excess return being –1.13% and October with 0.55%. Another mentionable trait in month-of-the-year strategies is the overall satisfactory performance of MOM portfolio during the time period of investigation. Overall returns of fundamental anomalies have been more favorable in the beginning of the year and at the end of the year, thus fully consistent with the documented half-year anomaly. Visualization of monthly dispersion of stock returns within factor portfolios is presented in **Appendix 7**.

Table 10. Average excess returns of each month within long-only top decile portfolios.

Mean excess returns of each month-of-the-year long portfolio. Decile portfolios are assumed to be zero cost, rebalancing done annually except for MOM and VAR portfolio monthly. Portfolios trading anomalies consist of U.S. stocks listed in NYSE, Amex and Nasdaq. Risk-free rate used to calculate each month's excess returns is 1-month U.S. treasury bill. For example, average excess return of

SIZE portfolio during January has been 5.28% between sample period from July 1963 to September 2019.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
SIZE	5,28	1,32	1,21	0,82	0,40	0,40	-0,34	-0,50	0,10	-1,51	0,62	0,96
BE/ME	3,44	1,13	1,79	1,94	0,08	-0,02	0,19	0,18	-1,02	-0,64	1,45	1,80
OP	1,19	0,30	0,83	1,20	0,46	0,20	0,21	0,11	-0,38	0,69	1,50	1,12
E/P	2,40	0,90	1,65	1,75	0,34	0,02	0,55	0,14	-0,12	-0,35	1,35	1,61
CF/P	2,46	0,83	1,71	2,06	0,35	0,04	0,15	0,37	-0,10	-0,47	1,07	1,57
D/P	1,67	-0,42	1,06	1,24	0,18	-0,10	0,70	1,17	0,25	0,17	0,40	0,69
MOM	1,48	1,45	1,45	1,44	1,00	1,02	0,09	0,49	0,33	0,25	2,13	2,15
ACC	2,04	0,60	1,05	1,24	0,15	0,07	0,44	0,30	0,07	-0,02	1,88	1,47
BETA	0,50	0,11	0,82	1,17	0,50	0,14	0,37	0,39	-0,11	1,04	0,80	0,99
ISS	0,83	0,59	1,27	1,00	0,14	-0,16	0,03	0,27	-0,32	0,79	0,97	1,48
VAR	0,43	0,11	0,84	0,88	0,19	0,02	0,31	0,48	0,17	0,60	0,99	0,91
Comp.	21,72	6,92	13,68	14,74	3,79	1,63	2,70	3,41	-1,13	0,55	13,16	14,75

Long-short factor portfolios have performed systematically worse compared to long portfolios. (**Table 11**) During January, SIZE and BE/ME portfolios have been ultimately superior compared to others in terms of excess returns. In October and July, VAR portfolio has performed better than other portfolios and moreover, the overall performance of portfolios have been the worst in November. Remarkably, MOM portfolio has notably outperformed other long-short portfolios in terms of returns in June with arithmetic average excess return of 2.43% and in December with arithmetic average excess return of 2.42%.

Table 11. Average excess returns of each month within long-short factor portfolios.

Mean excess returns of each month-of-the-year long-short portfolio. Decile portfolios are assumed to be zero cost, rebalancing done annually except for MOM and VAR portfolio monthly. Portfolios trading anomalies consist of U.S. stocks listed in NYSE, Amex and Nasdaq. Risk-free rate used to calculate each month's excess returns is 1-month U.S. treasury bill. For example, average excess return of SIZE portfolio on January has been 4.17% between July 1963 and September 2019.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
SIZE	4,17	0,94	0,09	-0,81	-0,16	0,03	-1,06	-0,94	0,28	-2,84	-0,93	-0,34
BE/ME	2,47	0,63	0,62	0,51	-0,73	-0,53	-0,19	-0,32	-0,72	-1,94	-0,33	0,58
OP	-1,94	-0,59	-0,4	0,02	0,37	0,15	0,79	-0,34	-0,12	1,24	-0,05	-0,61
EP	0,99	0,45	0,31	0,34	-0,64	-0,54	0,31	-0,51	0,42	-1,36	-0,72	0,49
CFP	1,19	0,29	0,41	0,64	-0,69	-0,44	0,04	-0,3	0,36	-1,38	-0,93	0,42
D/Y	0,27	-1,21	-0,34	-0,27	-0,72	-0,52	0,41	0,86	0,99	-0,41	-1,91	-0,95

MOM	-2,07	1,89	0,09	-0,83	1,31	2,43	0,83	0,02	1,86	1,15	1,54	2,42
ACC	0,46	-0,45	-0,09	-0,14	-0,42	0,05	0,83	-0,23	0,66	0,45	-0,33	0,22
BETA	-3,47	-0,77	-0,7	-0,14	0,2	0,64	0,41	-0,69	0,55	1,08	-1,65	-0,61
ISS	-1,14	0,13	0,56	0,11	-0,51	-0,03	0,46	0,18	0,13	0,54	-0,02	0,26
VAR	-3,45	0	0,11	-0,33	0,47	0,57	1,27	0,31	0,86	2,04	-0,72	0,19
Comp.	-2,52	1,31	0,66	-0,9	-1,52	1,81	4,1	-1,96	5,27	-1,43	-6,05	2,07

Table 12 shows the average monthly volatility of each individual month within fundamental anomalies. On average, high January returns exhibit also higher volatility compared to other months within long-only and long-short factor portfolios. In addition to this, volatility has been substantial within long-short factor portfolios during February, April, October and November. October has also exhibited substantial volatility within long portfolios. Comprehensively, June has the lowest volatility within portfolios, which can be partially due to the lower trading activity during summertime. (Jacobsen and Bouman, 2002).

Table 12. Monthly volatilities for month-of-the-year long-only and long-short decile portfolios trading anomalies.

In this table long-only decile portfolio volatility is number above and number below is long-short decile portfolio volatility (bolded) for each month. Volatilities are calculated as arithmetic average volatility of each month during the time period from July 1963 to September 2019. Volatilities are monthly figures. For example, average volatility of long-only SIZE portfolio during January is 7,53%. Figures do not include risk-free rate during out-of-the-market periods.

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
SIZE	7,53	6,25	4,98	6,12	6,02	5,44	5,44	5,79	5,8	7,65	6,27	5,19
	5,76	***5,55***	***4,5***	***4,67***	***4,63***	***4,08***	***3,89***	***3,62***	***3,67***	***4,44***	***4,43***	***4,2***
BE/ME	8,41	5,22	5,2	6,14	4,91	4,84	4,93	6,91	5,79	7,6	6,12	4,83
	6,5	***5,1***	***4,04***	***4,99***	***3,46***	***3,64***	***3,79***	***4,83***	***4,22***	***4,89***	***5,09***	***4,08***
OP	5,72	4,03	3,75	4,28	3,88	3,52	4,2	4,69	4,67	6,38	4,67	3,74
	4,4	***4,35***	***3,51***	***3,88***	***3,42***	***3,36***	***3,97***	***3,69***	***3,93***	***4,26***	***4,73***	***3,79***
E/P	7,16	4,53	4,55	4,3	4,6	4,2	4,66	5,68	5,35	6,85	5	4,12
	5,81	***4,77***	***3,21***	***3,54***	***3,39***	***4,05***	***3,96***	***2,98***	***3,95***	***5,32***	***4,48***	***4,13***
CF/P	7,07	4,59	4,65	4,28	4,46	4,4	4,58	5,86	5,47	6,5	5,11	4,31
	5,62	***4,91***	***3,44***	***3,78***	***3,08***	***3,92***	***4,05***	***3,32***	***4,21***	***4,98***	***3,99***	***4,29***
D/P	6,83	4,19	4,05	3,76	4,22	4,24	3,94	4,12	3,85	4,53	4,51	3,78
	7,22	***4,81***	***4,12***	***4,66***	***4,49***	***3,93***	***5,14***	***5,01***	***5***	***6,38***	***5,63***	***4,74***
MOM	7,25	5,66	4,98	5,29	5,57	4,96	5,76	6,23	6,21	8,42	6,63	5,32
	9,23	***6,64***	***7,33***	***8,97***	***6,68***	***5,74***	***5,76***	***5,87***	***5,71***	***6,52***	***6,73***	***6,19***

ACC	6,63	4,78	4,98	5,12	5,17	4,07	5,19	5,9	5,77	7,47	6,64	4,4
	3,5	***2,26***	***3,02***	***3,08***	***2,43***	***2,42***	***2,74***	***2,31***	***2,5***	***3,63***	***2,28***	***2,57***
BETA	3,8	3,31	2,99	2,62	2,91	3,32	3,32	3,97	3,45	4,73	3,24	2,81
	8,2	***6,94***	***4,96***	***5,96***	***5,32***	***4,46***	***6,5***	***6,29***	***7,2***	***7,67***	***7,45***	***5,32***
ISS	4,8	4,48	4,1	3,46	3,78	3,28	4,57	4,4	4,52	6,06	4,25	3,79
	3,16	***3,81***	***3,18***	***3,51***	***2,75***	***3,24***	***3,61***	***2,8***	***3,2***	***3,12***	***3,27***	***2,54***
VAR	3,96	3,22	2,53	2,93	2,97	2,79	3,24	3,6	3,15	4,24	3,3	2,9
	8,44	***9,26***	***7,56***	***8,62***	***6,54***	***6,6***	***6,24***	***6,53***	***7,53***	***8,11***	***9,56***	***6,38***
Avg.	6,29	4,57	4,25	4,39	4,41	4,10	4,53	5,20	4,91	6,40	5,07	4,11
	6,17	***5,31***	***4,44***	***5,06***	***4,20***	***4,13***	***4,51***	***4,30***	***4,65***	***5,39***	***5,24***	***4,38***

In Sharpe ratios portfolios are assumed to stay in the markets for one month in a year. Month-of-the-year portfolios' Sharpe and Adjusted Sharpe ratios are given in **Appendix 1**. From long portfolios, SIZE has been superior in January with SR of 2.447 and ASR of 4.588. This difference indicates highly positively skewed distribution of returns during January within SIZE portfolio. Moreover, CF/P portfolio during April has SR of 1.64 and ASR of 2.13 which indicates a solid performance of a portfolio during that time period according to these risk metrics and furthermore positive skewness of returns, which is desirable from investors' point of view. SR and ASR metrics comprehensively support previous findings, thereby these metrics tend to be at a better level in months within H1 compared those in H2. Furthermore, December has been sound performing month in terms of risk-adjusted returns within long portfolios, especially within MOM portfolio with SR of 1.396 and ASR of 1.773. Another interesting feature in MOM portfolio's risk-adjusted returns is the substantial difference between SR (1.000) and ASR (0.467) in March, indicating rather strong negative skewness in returns during that time period. Dispersion of risk-adjusted returns within long month-of-the-year portfolios support half-year anomaly, hence January, March, April and November exhibit systematically better risk-adjusted metrics than rest of the months, indicating that superior returns are not solely compensation for higher risk.

On the other hand, with long-short factor portfolios, SIZE and BE/ME portfolios within January have resulted in satisfactory risk-adjusted returns with ASR of 4.897 and 1.277. SR and ASR metrics for SIZE portfolio are at a higher level with long-short portfolio than long portfolio because long-short SIZE portfolio volatility has been notably lower compared to long portfolio volatility. Furthermore, long-short OP portfolio resulted in ASR of 1.177 during October which is significantly higher compared to long portfolio ASR of 0.337. In addition to this, long-short MOM portfolio has resulted in sound risk-adjusted returns in June with SR of 1.458 and ASR of 1.772 and December with SR of 1.356 and ASR of 1.772.

5.2.2.1. Regression results

Table 13 describes the results of dummy regression for each individual month within long-only top decile portfolios. We can see that January, March, April, November and December have been statistically superior months when considering excess returns over the risk-free instrument. Therefore, we can reject the null hypotheses that all monthly coefficients have the same value. Month-of-the-year regression results are astonishingly in line with half-year effect. On a yearly basis, time period of from May to Oct has generated rather insignificant returns and moreover in some instances even negative returns. January effect with size portfolio has generated statistically significant excess return of 5.3% at the confidence level of 99%. January has also been statistically significant month within BE/ME and CFP at same confidence level. Overall performance of size and value anomalies during January have been strong. Results of the January effect are in line with the research Rozeff and Kinney (1976), which pointed out the superior performance of January. The best performing portfolio in December has been MOM with a confidence level of 99%.

All portfolios, excluding SIZE, have performed well during April. Superior performance of April is consistent with earlier findings of Marrett and Worthington (2011). Thus, statistically significant performance of April within anomalies could partially be stemming from foreign tax-selling and re-allocating of funds as mentioned by Selvarani and Jenefa (2009). Compelling detail is also statistically significant performance of BETA, ISS and VAR portfolio in December and rather insignificant performance in January. This could be a consequence from capital re-allocation in the beginning of the year, thereby growth in risk-aversion towards the end of the year and *window dressing* of institutional investors at the yearend. Moreover, D/P portfolio generated statistically significant mean returns during August with a confidence level of 95. The Poor performance of portfolios between May and October could be linked to the vacations held during the summer months and lower trading activity as Jacobsen and Bouman (2002) found out. They suggested that monthly level of outbound travelling is significantly and inversely related to monthly level of stock returns. However, it seems highly unlikely, that substantial difference between summer months and non-summer months in other factor portfolios could be exhaustively explained with this single factor.

Table 13. Regression results of month-of-the-year anomaly within long-only top decile portfolios.

P-value of each regression is in parenthesis below. The dependent variable in each regression is the portfolios’ excess return over the risk-free rate of return whereas the independent variable is the dummy variable of each month. Number of observations is 675 with each regression. Regressions use Newey-West HAC corrected standard errors with lag m = 3. Statistically significant values are bolded and marked with asterisks when considered important. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively**.**

Long	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
SIZE	**0.053*****	0.013	**0.012***	0.008	0.004	0.004	-0.003	-0.005	0.001	-0.015	0.006	0.010
	(0.000)		(0.075)									
BE/ME	**0.034*****	0.011	**0.018****	**0.019****	0.001	-0.000	0.002	0.002	-0.010	-0.006	0.014*	**0.018*****
	(0.002)		(0.011)	(0.019)								(0.006)
OP	0.012	0.003	0.008	**0.012****	0.005	0.002	0.002	0.001	-0.004	0.007	**0.015****	**0.011****
				(0.037)							(0.016)	(0.027)
E/P	**0.024****	0.009	**0.016*****	**0.018*****	0.003	0.000	0.006	0.001	-0.001	-0.004	**0.013****	**0.016*****
	(0.012)		(0.007)	(0.003)							(0.045)	(0.004)
CF/P	**0.025*****	0.008	**0.017*****	**0.021*****	0.003	0.000	0.001	0.004	-0.001	-0.005	0.011	**0.016*****
	(0.009)		(0.007)	(0.000)								(0.007)
D/P	0.017*	-0.004	0.011*	**0.012****	0.002	-0.001	0.007	**0.012****	0.003	0.002	0.004	0.007
	(0.066)		(0.053)	(0.015)				(0.032)				
MOM	0.015	0.014*	**0.015****	**0.014****	0.010	0.010	0.001	0.004	0.003	0.002	**0.021****	**0.021*****
		(0.057)	(0.031)	(0.041)							(0.016)	(0.003)
ACC	**0.020****	0.006	0.011	0.012*	0.001	0.001	0.004	0.003	0.001	-0.000	**0.019****	**0.015****
	(0.021)			(0.073)							(0.034)	(0.013)
BETA	0.005	0.001	**0.008****	**0.012*****	0.005	0.001	0.004	0.004	-0.001	0.010	0.008*	**0.010*****
			(0.043)	(0.001)							(0.065)	(0.009)
ISS	0.008	0.006	**0.013****	**0.010****	0.001	-0.002	0.000	0.003	-0.003	0.008	0.010*	**0.015*****
			(0.023)	(0.030)							(0.088)	(0.004)
VAR	0.004	0.001	**0.008****	**0.009****	0.002	0.000	0.003	0.005	0.002	0.006	**0.010****	**0.009****
			(0.015)	(0.024)							(0.025)	(0.019)

Table 14 describes long-short factor portfolio month-of-the-year regressions. Remarkably, January effect among small capitalization stocks exists even in long-short portfolios, which have otherwise performed rather weakly during the period of investigation. Coefficient for long-short SIZE portfolio within January has been 4.2% and for BE/ME portfolio 2.5% which are statistically significant at the 1% risk level whereas same figures for long portfolios are 5.3% and 3.4%. Even though long-short strategy January returns are not equally substantial as long portfolio January returns for SIZE and BE/ME, findings are still intriguing due to the fact that in addition to MOM, they are only portfolios with statistically significant positive returns with a risk level of 1% among long-short portfolios. Otherwise long-short month-of-the-year factor portfolios have almost systematically underperformed the market return and long portfolio returns. Nevertheless, long-short OP portfolio has performed remarkably well during October with a coefficient of 0.012, significant at the 5% risk level. Another notable feature in the regressions is the outstanding success of long-short MOM portfolio within months of February, June, September and December. December and June coefficients of 0.024 are statistically significant at the confidence level of 99% indicating strong performance of long-short MOM portfolio. These results combined with results in **Table 5** on long-short H2 MOM portfolio's returns underline the relevance of momentum strategy, thus buying winner stocks and selling loser stocks in the U.S. market. In other words, MOM is the only long-short portfolio to achieve reasonable outcome. When comparing long and long-short MOM portfolio month-of-the-year regressions (**Table 13 and Table 14**), we can see that the contribution of short-selling loser stocks, thus contrarian strategy in MOM long-short portfolio, notably increases significance of obtained returns during February, June, September and December.

In **Appendix 11** month-of-the-year regressions are conducted based on excess return over the market portfolio for long-only top decile portfolios in order to examine on whether superior returns are caused by market seasonality effect described by Jacobsen *et al.* (2005). Remarkably, performance of SIZE, ACC and value portfolios (BE/ME, E/P and CFP) during January remain statistically significant compared to market portfolio performance ($p<0.05$). Therefore, January effect within value and size anomaly is not exhaustively explained by market seasonality effect in January. Moreover, similar results for value anomaly hold during March and April whereas abnormal returns inside fundamental anomalies in November and December are largely due to the market seasonality effect.

From long-short regressions, January effect within SIZE and BE/ME factor portfolios remains statistically significant even after accounting results for market seasonality. (**Appendix 12)** In addition to this, the performance of MOM long-short factor portfolio in June and September remains statistically significant ($p<0.05$). Nevertheless, results of long-short regressions are comprehensively somewhat insignificant with respect to long-only portfolio regressions.

Seasonal changes in market return have a substantial effect on the results of month-of-the-year regressions for long-only portfolios. Although, seasonal deviations in overall market performance can partially explain deviations in the returns of nested anomaly strategies, value anomaly and size effect are remarkable pervasive during the month of January and moreover, value anomaly have outperformed other portfolios and market portfolio also in March and partially in April. These findings support previous findings on value anomaly within half-year anomaly as a viable investing strategy.

Table 14. Regression results of month-of-the-year anomaly within long-short factor portfolios.

P-value of each regression is in parenthesis below. The dependent variable in each regression is the excess return over the risk-free rate of return whereas the independent variable is dummy variable of each month. Number of observations is 675 with each regression. Regressions use Newey-West HAC corrected standard errors with lag m = 3. Statistically significant values are bolded and marked with asterisks when considered important. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.

Long-short	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
SIZE	0.042***	0.009	0.001	-0.008	-0.002	0.000	-0.011**	-0.009*	0.003	-0.028***	-0.009	-0.003
	(0.000)						(0.041)			(0.000)		
BE/ME	0.025***	0.006	0.006	0.005	-0.007	-0.005	-0.002	-0.003	-0.007	-0.019***	-0.003	0.006
	(0.004)									(0.003)		
OP	-0.019***	-0.006	-0.004	0.000	0.004	0.002	0.008	-0.003	-0.001	0.012**	-0.000	-0.006
	(0.001)									(0.028)		
EP	0.010	0.005	0.003	0.003	-0.006	-0.005	0.003	-0.005	0.004	-0.014*	-0.007	0.005
CFP	0.012	0.003	0.004	0.006	-0.007*	-0.004	0.000	-0.003	0.004	-0.014**	-0.009*	0.004
										(0.039)		
D/P	0.003	-0.012*	-0.003	-0.003	-0.007	-0.005	0.004	0.009	0.010	-0.004	-0.019**	-0.009
											(0.012)	
MOM	-0.020*	0.019**	0.001	-0.010	0.013	0.024***	0.010	0.000	0.018**	0.011	0.015*	0.024***
	(0.096)	(0.034)				(0.002)			(0.014)		(0.085)	(0.004)
ACC	0.005	-0.004	-0.001	-0.001	-0.004	0.001	0.008**	-0.002	0.007**	0.004	-0.003	0.002
							(0.022)					
BETA	-0.035***	-0.008	-0.007	-0.001	0.002	0.006	0.004	-0.007	0.005	0.011	-0.017*	-0.006
	(0.002)											
ISS	-0.011***	0.001	0.006	0.001	-0.005	-0.000	0.005	0.002	0.001	0.005	-0.000	0.003
	(0.007)											
VAR	-0.035***	0.000	0.001	-0.003	0.005	0.006	0.013	0.003	0.009	0.020*	-0.007	0.002
	(0.002)									(0.059)		

5.3. Robustness check

Possible violation of data-snooping may affect the regression results. In addition to this, previously mentioned and widely recognized January effect can lead us strain, when observing half-year anomaly's existence among factor portfolio returns. Even macroeconomic fluctuations in the securities' return data can change the results in a way, that one may draw false conclusions on results. The aim of this section is to provide robustness checks for previously drawn results.

Partially due to the similarity of portfolios formation rules and tendency of overall stock markets to exhibit somewhat high volatility compared to other asset classes, some portfolios exhibit very high levels of correlation. **Table 15** represents a correlation matrix of long-only top decile portfolios. SIZE portfolio has highest correlation with BE/ME portfolio, which is consistent with Fama and French (1993) research. There is a strong correlation between all value anomalies within long portfolios as well as low risk portfolios BETA and VAR are highly correlated. Another mentionable relation is between ACC and OP portfolios with moderately high correlation coefficient of 0.854 and ISS and OP with correlation coefficient of 0.864.

Table 15. Correlation matrix of the long-only top decile portfolios.

	SIZE	BE/ME	OP	E/P	CF/P	D/P	MOM	ACC	BETA	ISS	VAR
SIZE	1										
BE/ME	0,782	1									
OP	0,691	0,722	1								
E/P	0,746	0,871	0,789	1							
CF/P	0,730	0,851	0,768	0,947	1						
D/P	0,513	0,694	0,591	0,698	0,673	1					
MOM	0,756	0,678	0,796	0,725	0,728	0,415	1				
ACC	0,779	0,749	0,854	0,790	0,793	0,520	0,841	1			
BETA	0,481	0,616	0,746	0,695	0,681	0,699	0,596	0,650	1		
ISS	0,640	0,742	0,864	0,783	0,784	0,660	0,725	0,793	0,792	1	
VAR	0,495	0,629	0,753	0,725	0,691	0,758	0,551	0,640	0,876	0,796	1

There is no significant correlation between long-short factor portfolios with respect to long portfolios. (**Table 16**) Nevertheless, correlation is often negative between portfolios and the highest correlation is between value factor portfolios. The modest amount of correlation between long-short factor portfolios could be stemming from the fact that, excluding value portfolios, different portfolios short-sell very different equities in the market and therefore different stocks react to changes in market environment differently.

Table 16. Correlation matrix of the long-short factor portfolios.

	SIZE	BE/ME	OP	E/P	CF/P	D/P	MOM	ACC	BETA	ISS	VAR
SIZE	1										
BE/ME	0,390	1									
OP	-0,547	-0,329	1								
E/P	0,153	0,661	0,039	1							
CF/P	0,159	0,663	0,015	0,865	1						
D/P	-0,045	0,366	0,156	0,503	0,471	1					
MOM	-0,088	-0,254	0,173	-0,069	-0,063	-0,184	1				
ACC	-0,132	0,011	-0,040	0,042	0,096	0,076	0,164	1			
BETA	-0,523	-0,122	0,578	0,188	0,163	0,521	0,232	0,137	1		
ISS	-0,448	-0,077	0,490	0,101	0,130	0,260	0,109	0,079	0,567	1	
VAR	-0,577	-0,141	0,674	0,226	0,162	0,463	0,239	0,089	0,852	0,585	1

5.3.1. Effect of January and macro-economic fluctuations

Previous results indicate a strong half-year effect among factor portfolios, especially within long-only top decile portfolios. Results also underline the persistency of January effect in the U.S. markets similarly as Haugen and Jorion (1996) suggested. In order to obtain more robust conclusion on half-year effect, regressions are carried on in a similar manner to Maberly and Pierce (2004), thus controlling January from the results. In regression equation (13) $D_t - Jan_t$ acts as half-year dummy for period H1 excluding January and $\gamma_t * Jan_t$ as dummy variable for January, thus 1 if January and 0 otherwise. Dependent variable is portfolios' excess return over the market portfolios' return.

$$R_t - Rm_t = \mu_i + \beta_i * (D_t - Jan_t) + \gamma_t * Jan_t + \varepsilon_i \tag{13}$$

Half-year anomaly remains statistically significant within value anomaly even after controlling for January returns. (**Table 17**) Furthermore, size effect is completely explained by January effect and it disappears when excluding January returns from the data. Thus, consistent with earlier findings (e.g., see Malkiel, 1999; Thaler, 1987), January effect plays a substantial role especially within small capitalization stocks. After the adjustment long MOM portfolio coefficient remains statistically significant at the confidence level of 99%. Exhaustively, regression results underline the superiority of value investing in H1. Especially BE/ME portfolio have achieved significant results (*p<0.01*) even after controlling for January returns and moreover it has performed significantly better than market portfolio in H1. From the results of **Table 17** we can conclude, that half-year anomaly within BE/ME, E/P,CF/P, MOM and ACC portfolios is not predominantly caused by January effect or overall market seasonality effect. Moreover, regression results in **Table 17** offer a persuasive evidence of superior returns in January within portfolios of SIZE, BE/ME, and CF/P at the risk level of 1%.

Table 17. Half-year effect with January controlled.

Regressions use Newey-West corrected standard errors (lag=3). Coefficient p-value in parentheses. Statistically significant values are bolded and marked with asterisks when considered important. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

H1-Jan	LONG				LONG-SHORT			
	H1		Jan		H1		Jan	
SIZE	0,0003		**0,0411*****	(0.000)	**-0,012*****	(0.000)	**0,0301*****	(0.000)
BE/ME	**0,007*****	(0.003)	**0,023*****	(0.001)	-0,005		0,0131	
OP	0,0003		0,0002		**-0,0128*****	(0.001)	**-0,031*****	(0.001)
E/P	**0,005*****	(0.002)	**0,0123****	(0.011)	-0,0078*	(0.051)	-0,0016	
CF/P	**0,0049*****	(0.005)	**0,0129*****	(0.005)	**-0,007****	(0.050)	0,0002	
D/P	-0,003		0,005		**-0,019*****	(0.000)	-0,008	
MOM	**0,007*****	(0.000)	0,003		0,0006		**-0,032****	(0.029)
ACC	**0,002****	(0.039)	**0,0088****	(0.024)	**-0,011*****	(0.000)	-0,007	
BETA	-0,001		-0,006		**-0,017*****	(0.002)	**-0,046*****	(0.005)
ISS	0,001		-0,003		**-0,007****	(0.049)	**-0,023****	(0.014)
VAR	-0,0021		-0,007	(0.082)	-0,011		**-0,046*****	(0.005)

Another approach to take when investigating the significance of half-year anomaly is by controlling results for different macro-economic conditions. This adds robustness to research findings, because large market crashes have often occurred within period of H2 as Maberly and Pierce (2004) described in their research. By controlling periods of recession in factor portfolios' returns data we can conclude on whether they act as catalysator behind the poor performance of H2 compared to H1 in a long run. Regressions with controlling for recession are proceed as following.

$$R_t - Rm_t = \mu_i + \beta_i * (D_t - Recession_t) + \gamma_t * Recession_t + \varepsilon_i \tag{14}$$

In equation (14), periods of recession or economic contraction are marked with dummy variable $\gamma_t * Recession_t$ and dummy variable for period H1 and H2 $\beta_i * (D_t - recession_t)$ excluding the periods of recessions. Dependent variable is portfolios' excess return over the market portfolios' return.

Table 18. Recession controlled regressions for half-year anomaly within long-only top decile portfolios.

Regressions use Newey-West corrected standard errors (lag=3). Statistically significant values are bolded and marked with asterisks when considered important. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

LONG	H1		H2		Recession
SIZE	**0,0088*** **	(0.001)	-0,0003		-0,002
BE/ME	**0,009*** **	(0.000)	-0,002		0,002
OP	0,0004		0,0007		0,002
E/P	**0,005*** **	(0.000)	0,0008		0,003
CF/P	**0,006*** **	(0.000)	0,0005		0,001
D/P	-0,007		0,003*	(0.068)	-0,001
MOM	**0,007*** **	(0.000)	**0,004*** **	(0.006)	0,001
ACC	**0,0045*** **	(0.002)	0,0016		-0,001
BETA	-0,0025		0,001		0,004
ISS	0,0001		0,0004		0,0009
VAR	-0,003*	(0.058)	0,001		0,003

From **Table 18** we can draw the conclusion that half-year anomaly exists after controlling returns with periods of economic contraction. H1 long-only portfolio coefficients and statistical significance of them systematically increased after controlling results with recession periods. However, H2 period coefficients did not exhibit similar enhancement as H1 coefficients after the adjustment. According to obtained results, periods of economic contraction does not have a substantial effect on previous results documented in this thesis. Therefore, results are somewhat inconsistent with the findings of Maberly and Pierce (2004) and moreover, consistent with the earlier findings on half-year anomaly (e.g., see Bouman and Jacobsen, 2002; Lean, 2011; Andrade *et al*., 2013).

Recession controlled long-short factor portfolio results are predominantly similar as previous findings in this thesis. (**Table 19**). Controlling regressions for recession underlines the robustness of previously recorded H2 long-short MOM strategy at the confidence level of 95%. Results in **Table 19** therefore indicate, that in addition to long-only position, short-selling strategy within MOM portfolio generates sound outcome.

Table 19. Recession controlled regressions for half-year anomaly within long-short factor portfolios.

Regressions use Newey-West corrected standard errors (lag=3). Statistically significant values are bolded and marked with asterisks when considered important. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

LONG-SHORT	H1		H2		Recession
SIZE	-0,004		**-0,01*** **	(0.000)	0,0004
BE/ME	-0,004		**-0,009*** **	(0.001)	0,007
OP	**-0,017*** **	(0.000)	-0,0006		0,008
E/P	**-0,009*** **	(0.007)	**-0,006** **	(0.027)	0,0103
CF/P	**-0,008** **	(0.019)	**-0,006** **	(0.029)	0,007
D/P	**-0,018*** **	(0.000)	-0,002		0,006
MOM	-0,003		**0,007** **	(0.048)	0,013
ACC	**-0,011*** **	(0.000)	-0,0002		0,005
BETA	**-0,024*** **	(0.000)	-0,0016		0,009
ISS	**-0,012*** **	(0.000)	-0,002		0,0104
VAR	**-0,02*** **	(0.001)	0,004		0,02

5.3.2. Multi-Factor model and liquidity premium

The purpose of this sub-section is to identify the most dominant risk factor that explain the returns of anomalies and examine on whether half-year anomaly has significant explanatory power after controlling returns of each anomaly with widely recognized risk factors.

Multi-Factor model is ultimately based on CAPM. In addition to CAPM, risk factors of three factor model (Fama and French 1993), momentum factor *MOM* of Carhart (1997), traded liquidity factor *LIQ* of Pastor and Stambaugh (2003) and profitability factor *RMW* are added into regression. Profitability factor describes the average return of two portfolios of companies with robust profitability minus average return of two portfolios with weak operating profitability companies. D_t represents the half-year dummy (H1). Equation (15) describes utilized multi-factor model.

$$R_t - Rf_t = \alpha_i + \beta_{1i}(R_{mt} - R_{ft}) + \beta_{2i}(SMB_t) + \beta_{3i}(HML_t) + \beta_{4i}(MOM_t) + \beta_{5i}(LIQ_t) + \beta_{6i}(RMW_t) + \beta_{7i}(D_t) + \varepsilon_i \tag{15}$$

In previous regressions in this thesis intercept is dropped out in each regression to avoid beforementioned *dummy trap*. However, in factor model alpha α_i is the intercept, describing the return that is not explained by common risk factors. Thus, statistical significance of alpha implies that there may be some crucial explanatory factors left outside the regression model. Objective of multifactor model in this thesis is to observe on whether H1 period has explanatory power after six-factor model is employed with it. Explanatory power of H2 period is included in constant term, thus it is not reported separately.

Table 20. Multifactor model for long-only top decile portfolios.

Risk factors used in these regressions are similar as in Fama and French (1993), Carhart (1997), Pastor and Stambaugh (2003). Data used in regressions consist of U.S. securities data from January 1968 to December 2018. P-values in parentheses. Regressions use Newey-West corrected standard errors (lag=3). Statistically significant values are bolded and marked with asterisks when considered important. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

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LONG	Intercept	Market	SMB	HML	RMW	MOM	LIQ	H1	Adj. R-Squared
SIZE	-0,002	**0,873*****	**1,139*****	**0,082*****	**-0,244*****	0,003	0,049	0,001	92,65 %
		(0.000)	(0.000)	(0.019)	(0.000)				
BE/ME	0,001	**1,175*****	**0,390*****	**0,871*****	**-0,151*****	-0,09	**-0,114****	**0,003****	88,58 %
		(0.000)	(0.000)	(0.000)	(0.003)	(0.044)	(0.014)	(0.045)	
OP	-0,001	**0,995*****	0,018	**-0,128*****	**0,446*****	0,006	0,003	0,001	92,80 %
		(0.000)		(0.000)	(0.000)				
E/P	-0,001	**1,086*****	**0,291*****	**0,589*****	**0,246*****	-0,005	0,004	0,001	85,70 %
		(0.000)	(0.000)	(0.000)	(0.000)				
CF/P	-0,001	**1,064*****	**0,257*****	**0,575*****	**0,234*****	0,015	-0,018	0,002	82,22 %
		(0.000)	(0.000)	(0.000)	(0.000)				
D/P	**0,005****	**0,768*****	0,007	**0,773*****	**0,1**	**-0,142*****	-0,044	**-0,008*****	67,72 %
	(0.021)	(0.000)		(0.000)		(0.000)		(0.000)	
MOM	**0,003****	**1,146*****	**0,0324*****	**-0,134*****	**-0,150****	**0,551*****	**-0,088****	0,000	91,55%
	(0.017)	(0.000)	(0.000)	(0.000)	(0.020)	(0.000)	(0.024)		
ACC	0,003*	**1,088*****	**0,242*****	**-0,146*****	-0,057	0,038	**-0,089*****	0,002	86,25 %
	(0.068)	(0.000)	(0.000)	(0.001)			0.041		
BETA	0,002*	**0,716*****	**-0,221*****	**0,251*****	**0,126****	**0,056***	-0,028	-0,002	70,54 %
	(0.088)	(0.000)	(0.000)	(0.000)	(0.020)	(0.096)			
ISS	-0,001	**0,967*****	**-0,116*****	**0,144*****	**0,223*****	-0,001	-0,009	0,002	84,67 %
		(0.000)	(0.001)	(0.000)	(0.000)				
VAR	0,001	**0,689*****	**-0,163*****	**0,299*****	**0,195*****	0,021	-0,018	-0,001	72,52 %
		(0.000)	(0.000)	(0.000)	(0.000)				

From **Table 20**, we can see, that when employing commonly used risk factor as explanatory variables the statistical significance of H1 period in explaining returns within long-only portfolios systematically declines. However, H1 explanatory variable is statistically significant at the 5% risk level with BE/ME portfolio, which underlines the gravity of H1 period in explaining BE/ME portfolio returns. This outcome is consistent with previously obtained results on BE/ME portfolio in this thesis. Regression results provide a solid footing for the results of my predecessors Fama and French (1993), thus Market, SMB, HML and RMW are statistically significant explanatory variables in almost every portfolios' returns.

Table 21. Multifactor model for long-short factor portfolios.

Risk factors used in these regressions are similar as in Fama and French (1993), Carhart (1997), Pastor and Stambaugh (2003). Data used in regressions consist of U.S. securities data from January 1968 to December 2018. P-values in parentheses. Regressions use Newey-West corrected standard errors (lag=3). Statistically significant values are bolded and marked with asterisks when considered important. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

6-FM LONG-SHORT	Intercept	Market	SMB	HML	RMW	MOM	LIQ	H1	Adj. R-Squared
SIZE	**-0,005*** **	**-0,104*** **	**1,413*** **	**0,093*** **	**-0,276*** **	0,001	0,027	0,002	87,01 %
	(0.000)	(0.000)	(0.000)	(0.007)	(0.000)				
BE/ME	**-0,00371**	**0,462*** **	**1,356*** **	**-0,337*** **	-0,075*	-0,087*	0,003*	**-0,004** **	77,96 %
	(0.036)**	(0.000)	(0.000)	(0.000)	(0.072)	(0.079)	(0.090)	(0.036)	
OP	**-0,005*** **	**-0,312*** **	-0,024	**1,271*** **	0,021	0,058	0	**-0,005*** **	75,16 %
	(0.003)	(0.000)		(0.000)				(0.003)	
E/P	**-0,0072*** **	**0,297*** **	**1,108*** **	**0,289*** **	0,022	0,052	0,001	**-0,007*** **	56,40 %
	(0.002)	(0.000)	(0.000)	(0.000)				(0.002)	
CF/P	**-0,006*** **	**0,289*** **	**1,065*** **	**0,251*** **	0,04	0,001	0,001	**-0,006*** **	53,38 %
	(0.005)	(0.000)	(0.000)	(0.001)				(0.005)	
D/P	0,002	-0,029	**1,010*** **	**-0,174*** **	**-0,154*** **	0,066	**-0,011*** **	0,002	53,42 %
			(0.000)	(0.068)	(0.002)		(0.001)		
MOM	0,000	-0,047	-0,050	-0,022	0,115	**1,508*** **	-0,013	-0,001	84,71 %
						(0.000)			
ACC	0,003	**-0,204*** **	0,068	**-0,227*** **	**0,105*** **	-0,034	-0,002	0,003	8,41 %
		(0.000)		(0.002)	(0.002)				
BETA	0	**-0,847*** **	**0,478*** **	**0,371*** **	**0,236*** **	-0,038	-0,003	0	70,14 %
		(0.000)	(0.000)	(0.001)	(0.000)				
ISS	-0.001	**-0,348*** **	**0,190*** **	**0,333*** **	0,047	-0,005	0,004	-0,001	35,81 %
		(0.000)	(0.000)	(0.000)			(0.065)*		
VAR	0,001	**-0,969*** **	**0,645*** **	**1,048*** **	**0,261*** **	0,002	0	0,001	73,04 %
		(0.000)	(0.000)	(0.000)	(0.005)				

Long-short factor portfolios of BE/ME, OP, E/P and CF/P have statistically significant H1 variables in multifactor model suggesting a poor performance of factor portfolios during H1. (**Table 21**) Based on these results a conclusion can be drawn that during H1 long-short portfolios, especially value anomaly, have performed poorly. Constant term is statistically significant with portfolios of SIZE, BE/ME, OP, E/P and CF/P indicating, that in addition to poor performance of H1, H2 period or some other explanatory variable may be left outside the regression equation. The same independent variables explain the most of the returns in long-short factor portfolios as in long-only portfolios and moreover, explanatory power of dummy variable H1 is generally marginal compared to other risk factors.

Market wide liquidity measures of Stambaugh and Pastor (2003) is employed to examine difference between liquidity in the markets during H1 and H2. **Table 22** shows, that there is no statistically significant difference in aggregate liquidity or in traded liquidity in the markets between H1 and H2 period. Therefore, a conclusion can be drawn that the documented half-year anomaly is not stemming from market-wide liquidity differences between H1 and H2 period.

Table 22. Pastor and Stambaugh liquidity measures of H1 and H2 and Welch's t-statistic.

Statistically significant values are bolded and marked with asterisks when considered important. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.) Liquidity measures available at: https://faculty.chicagobooth.edu/lubos-pastor/data.

From January 1968 – December 2018	H1	H2	TStat
Aggregate Liquidity	0,0444	0,0481	(-0,9249)
Traded Liquidity	0,0269	0,0246	(1,3449)

5.3.3. Sub-periods

In order to conclude on whether half-year anomaly exists within anomalies throughout the time-period between 1963 and 2019, sub-period dummy regressions are conducted. Period 1 consist of portfolio returns between July 1963 to December 1990 and period 2 from January 1991 to September 2019. In sub-period regressions the dependent variable is portfolios' excess return over the market portfolios' return.

Table 23. Period 1 regressions for long-only and long-short factor portfolios.

Data used in regressions consist of U.S. securities data 1963 and 2019. Period 1 consist of portfolio returns between July 1963 and December 1990 (N=330). P-values in parentheses. Regressions use Newey-West corrected standard errors (lag=3). Statistically significant values are bolded and marked with asterisks when considered important. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

	LONG				LONG-SHORT			
Period 1	H1		H2		H1		H2	
SIZE	**0,009*****	(0.005)	-0,005*	(0.092)	-0,002		**-0,0104****	(0.014)

BE/ME	**0,0102*** **	(0.000)	-0,001		-0,001		-0,004	
OP	0,0004		0,0003		**-0,0201*** **	(0.000)	0,004	
E/P	**0,006*** **	(0.004)	-0,0008		-0,007		-0,003	
CF/P	**0,006*** **	(0.002)	0,0012		-0,006		-0,0009	
D/P	-0,0006		0,003		**-0,0169*** **	(0.008)	-0,0002	
MOM	**0,0104*** **	(0.000)	0,004*	(0.089)	0,003		**0,012** **	(0.029)
ACC	**0,004** **	(0.031)	0,0001		**-0,0105** **	(0.020)	0,0008	
BETA	-0,002		0,004*	(0.052)	**-0,023*** **	(0.004)	0,007	
ISS	0,0007		-0,001		**-0,011** **	(0.028)	-0,0005	
VAR	-0,002		0,0017		**-0,016** **	(0.043)	0,013*	(0.071)

Table 22 and **Table 23** provide ample support for earlier results provided in this thesis and especially illustrates the robustness of value anomaly within half-year anomaly. Long-only value portfolios of BE/ME, CF/P and E/P have statistically significant H1 coefficient at the risk level of 1% in period 1, whereas coefficients of H2 are mostly insignificant in explaining returns of long-only portfolios. The performance of these value portfolios has been stabile from period 1 to period 2. Thus, coefficients of BE/ME and E/P remain statistically significant at the risk level of 1% in period 2 and coefficient of CF/P at the risk level of 5% in period 2. Interestingly, SIZE portfolio H1 coefficient has faced regressive development from period 1 (0.009, $p<0.01$) to period 2 (0.004). In a similar manner H1 MOM portfolio in period 1 has performed better than period 2 indicating, that H1 MOM portfolios' returns have weaken in recent decades. Moreover, previously recorded H2 MOM long-short factor portfolio has generated statistically significant returns in period 1 ($p<0.05$). However, in period 2 the significance of the returns of this portfolio has modestly decreased. Otherwise all long-short factor portfolios have performed poorly.

Table 24. Period 2 regressions for long-only and long-short factor portfolios.

Data used in regressions consist of U.S. securities data 1963 and 2019. Period 2 consist of portfolio returns between January 1991 and September 2019 (N=345). P-values in parentheses. Regressions use Newey-West corrected standard errors (lag=3). Statistically significant values are bolded and marked with asterisks when considered important. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

	LONG				LONG-SHORT			
Period 2	H1		H2		H1		H2	
SIZE	0,004		-0,001		-0,007		-0,007*	(0.092)

BE/ME	**0,0085****	(0.018)	-0,004		-0,003		**-0,011*****	(0.005)
OP	0,0002		0,002*	(0.053)	-0,0116*	(0.055)	0,0013	
E/P	**0,006*****	(0.000)	0,001		-0,006		-0,006	
CF/P	**0,005****	(0.013)	-0,0016		-0,006		-0,008*	(0.059)
D/P	-0,003		0,003		**-0,017*****	(0.003)	0,0008	
MOM	0,0036		**0,005****	(0.038)	-0,0125		0,0112*	(0.097)
ACC	0,0035*	(0.079)	0,0016		**-0,0103*****	(0.002)	0,002	
BETA	-0,003		0,001		**-0,021*****	(0.003)	-0,001	
ISS	-0,00007		0,002		-0,008*	(0.069)	0,0015	
VAR	-0,003		0,0025		-0,017*	(0.074)	0,003	

Conclusively, long-only value portfolios (BE/ME, E/P and CF/P) are the only portfolios that have generated superior returns in H1 period during the whole sample period and moreover we cannot affiliate these returns with seasonal deviations in market portfolios' performance. These results are consistent with earlier findings of Andrade *et al*. (2013) who investigated half-year anomaly globally between time period of 1998 and 2012.

Appendix 3 and **Appendix 4** describe month-of-the-year regression results of period 1 and 2 for long-only top decile portfolios. These tables show that January effect have remained statistically significant in small capitalization stocks, although otherwise gradually diminished from value portfolios from period 1 to period 2. Thus January effect in SIZE portfolio is not dependent on the investigation period or market seasonality effect. In addition to this, value portfolios (BE/ME, E/P, CF/P) have performed significantly better in March and April during period 2 with respect to period 1. Although, in period 1 April and November in MOM portfolio are statistically significant in explaining excess returns over the market portfolio at the risk level of 1%, there is no significant month-of-the-year effect in MOM portfolio returns in period 2. Sub-sample regressions for month-of-the-year long-short factor portfolios are displayed in **Appendix 5** and **Appendix 6**. January effect in small capitalization stocks is present in period 1 but not in period 2. Otherwise, there is no mentionable month-of-the-year effect present in long-short factor portfolios with respect to market portfolio performance.

Comprehensively, the results of the sub-sample regressions are not equivalently significant as those concerning the whole sample. However, these results still support previous findings on the superiority of value anomaly within calendar anomalies and January effect within small capitalization stocks. Sub-period investigation offers us a pragmatic view on investing possibilities within nested anomaly strategies. Should have investor selected a nested value anomaly strategy based on period 1 regression results, investor's expected return would have been somewhat the same during period 2 according to results of period 2 regressions. However, as many researchers before (e.g., see Keim, 2003; Malkiel, 1999) have found out, strategies trading anomalies can be hard-to-profit strategies, for the results of this study are that of zero-cost portfolios. When including opportunity costs, taxes, bid-ask spreads, trading fees and other transaction costs brought by trading volume, time consumption and illiquidity in some instances results may amend in one way or another. Especially in MOM and VAR portfolios where rebalancing is done monthly dilution effect caused by these cost could be significant.

5.3.4. GARCH-model

Generalized autoregressive conditional heteroscedasticity model (GARCH) is employed in order to capture the time varying volatility of the time series of each portfolio. (Bollerslev, 1986) This thesis utilizes univariate GARCH (*p,q*) with a lag length of (1,1), which is often find sufficient with financial datasets (Lean, 2011). Value *p* represents the lagged squared error term whereas *q* previous value of conditional variance. GARCH (1,1) model suggests that current value *t* of time-series is dependent on *t-1* variance and error term. Equations for GARCH (1,1) model are constructed as following.

$$R_t - R_{ft} = \mu_i + \beta_i D_t + \lambda_i \sigma_t^2 + \varepsilon_i \tag{16}$$

$$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \alpha_2 \sigma_{t-1}^2 \tag{17}$$

In equation (16) λ_i is the parameter for conditional variance σ_t^2. In equation (17) α_0 is the constant, whereas α_1 and α_2 are parameters for lagged squared error term and lagged variance. Dependent variable $R_t - R_{ft}$ is portfolios' excess return over the risk free rate of return.

Parameters in GARCH model are estimated simultaneously using maximum likelihood method. More specifically, numerical maximization is done with log likelihood function with STATA software. GARCH-in-mean model is obtained by combining mean-equation model (16) and conditional variance model (17). Therefore, from equation (17) conditional variance σ_t^2 is used as explanatory variable in equation (16).

Table 25. GARCH-in-mean model within fundamental anomalies.

Conditional variance model GARCH (1,1) within long-only top decile portfolios. Statistically significant values are bolded and marked with asterisks when considered important. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

	Cons.	H1(β_i)	α_0	α_1	α_2	$\alpha_1 + \alpha_2$
SIZE	-0.0021	**0.0187*** **	**0.0004*** **	**0.0990*** **	**0.8001*** **	0,8991
BE/ME	0.00038	**0.018*** **	**0.0003*** **	**0.1133*** **	**0.8121*** **	0,9254
OP	-0.0030	**0.0075** **	**0.0001** **	**0.0919*** **	**0.8609*** **	0,9528
E/P	0.0026	**0.0130** **	**0.00017*** **	**0.0555*** **	**0.8797*** **	0,9352
CF/P	0.0029	**0.0135*** **	**0.0002*** **	**0.0842*** **	**0.8384*** **	0,9226
D/P	**0.0065*** **	0.0035	**0.00014** **	**0.1608*** **	**0.7614*** **	0,9222
MOM	**0.006** **	**0.0112** **	**0.0007** **	**0.1565*** **	**0.6544*** **	0,8109
ACC	0.0035	**0.0113*** **	**0.0002** **	**0.0880*** **	**0.8485*** **	0,9365
BETA	**0.0045*** **	0.0031	**0.0001*** **	**0.1152*** **	**0.7928*** **	0,9080
ISS	0.0038*	**0.0062** **	**0.0001*** **	**0.1356*** **	**0.8065*** **	0,9421
VAR	**0.0042*** **	0.0039*	**0.00008** **	**0.1256*** **	**0.8081*** **	0,9337

Previous results have indicated predominantly poor performance of long-short factor portfolios. Therefore, conditional variance is model is conducted solely on long-only portfolios. Results in **Table 25** indicate, that half-year anomaly appears in factor-portfolios with conditional variance model. These results support previous findings on half-year anomaly. However, D/P, VAR and BETA portfolio does not exhibit statistically significant H1 coefficient with GARCH (1,1) model. Based on the weak performance of H1 coefficient within these portfolios we can conclude, that these portfolios tend to exhibit strong time varying risk premium which can to some extent explain anomalous risk-adjusted returns. Moreover, these portfolios tend to have more significant returns during remainder of the year compared to period of H1 with conditional variance model. Stationarity condition $\alpha_1 + \alpha_2 < 1$ holds with every portfolio returns. Stationary condition measures the level of volatility persistence, thus more than 1 indicates explosive effect of volatility which means, that future expected conditional variance is largely affected by distant past information shocks and volatility. However, numerical values in **Table 25** are close to 1, indicating that volatility has highly persistent effect and therefore high levels of volatility decay slowly. There is a strong ARCH (α_1) and GARCH (α_2) effect present in all the factor portfolios, thus all portfolios exhibit statistically significant lagged squared error term and lagged variance term in GARCH in mean-model at the confidence level of 99%. Therefore, we can conclude, that there is a time varying risk premium in the U.S. market, which can partly explain anomalous excess returns within nested anomalies. However, BE/ME portfolio and SIZE portfolio have the highest values of H1 coefficient, 0.018 and 0.0187, indicating stronger half-year effect within these portfolios with respect to other portfolios.

6. CONCLUSIONS

This thesis examines half-year anomaly and month-of-the-year effect within fundamental anomalies based on firm specific factors of size, book equity to market equity, operating profitability, earnings to price, cashflow to price, dividend yield, momentum, accruals level, net share issuances, beta coefficient and variance of stock price. Absolute returns and risk-adjusted returns of each nested anomaly strategy is investigated and moreover, statistical significance of results is examined with regression models.

Findings implicate strong half-year effect within fundamental anomalies. Therefore, strategies trading fundamental anomalies within calendar anomalies are robust in the U.S. stock market. Results support previous empirical findings on different anomalies and calendar anomalies. Compared to conservative buy-and-hold strategy, half-year anomaly has proven to exhibit superior opportunities in terms of returns in value, momentum and small capitalization securities. In fact, z-values show that only long-only buy-and-hold portfolios that have significantly outperformed the market portfolio are E/P and MOM portfolios. Evidence also show that half-year anomaly coefficients significantly differs from zero with most of the long portfolios and moreover, that month-of-the-year dispersion of stock returns within U.S. markets also support half-year anomaly.

The most prominent finding in this thesis is the outstanding performance of BE/ME portfolio within H1 holding period. Thus, in terms of absolute and risk-risk-adjusted returns, long-only top decile portfolio based on company's high level of book equity to market equity has been superior within half-year anomaly holding period from November to April between 1963 and 2019. This portfolio has generated monthly excess return of 0.9% over the market portfolio. The empirical investigation in this thesis proves that this result do not alter due to changes in macro-economic environment and that the January effect documented by Rozeff and Kinney (1976) does not explicate the superior performance of the BE/ME portfolio. Furthermore, Jobson-Korkie z-values demonstrate, that there is a statistically significant difference in risk-adjusted returns between half-year BE/ME, E/P and CF/P long-only portfolios compared to market portfolio. Thus, value anomaly combined with half-year anomaly is a superior investing strategy compared to other anomalies and even compared to value investing with buy-and-hold principle. Empirical results also show that this seasonality effect within value anomaly portfolios is not caused by market seasonality effect suggested by Jacobsen *et al*. (2005). Results also underline a strong performance of small capitalization companies during the half-year holding period (H1). Seasonal deviations in market portfolio returns did not fully explain this effect. However, this thesis proves that half year anomaly within small capitalization portfolio is largely caused by the January effect.

Results of this thesis also reveal somewhat strong low risk anomaly within H2 holding period on a yearly basis. According to z-values, H2 long-only portfolios of BETA, VAR and MOM have generated statistically superior risk-adjusted returns compared to market portfolio. Low-risk anomalies also tend to provide investor with a better absolute return during H2 period compared to rest of the year. Behind this may be more active trading during the winter season and therefore, inflated lottery demand mentioned by Bali (2017). Thus, stocks with high volatility levels and risk gather investors' interest, thereby causing mispricing of low risk stocks. In addition to this, the long-only top decile portfolio based on low level of net share issuances of company has performed significantly better during H1 period annually compared to the rest of the year, thus supporting the market timing hypotheses of company's' optimal capital structure. Long-only MOM portfolio has also performed well during H1 achieving significant risk-adjusted returns. Predominantly long-short strategies have not been worthwhile in terms of risk-return relationship. However, according to z-values and regression results long-short MOM strategy during H2 period has generated significantly better returns compared to other long-short factor portfolios and moreover, better risk-adjusted returns compared to overall market performance with the excess return of 1.18% over the market portfolio. However, results of momentum portfolios are likely to face rather substantial dilution when taking costs of trading and short-selling into account, hence rebalancing of the portfolio is proceeded on a monthly basis.

From month-of-the-year results January proves itself to be a superior month in terms of risk-adjusted returns. Previous empirical findings also support this result. (e.g., see Rozeff and Kinney, 1976; Keim, 1985; Haugen and Jorion, 1996) Especially companies with small capitalization and high level of book equity to market equity have persistently generated excess returns during January. Moreover, value anomaly has outperformed other anomalies and market portfolio during March and April. In addition to this, mean stock returns within all anomalies have comprehensively been favorable for investor during April on a yearly basis.

I discussed issues related to the results of calendar anomalies that previous researchers have pointed out. (e.g., see Maberly and Pierce, 2004; Bouman and Jacobsen, 2002) The results documented by this thesis hold, even after controlling results with macro-economic conditions and January effect. Furthermore, half-year anomaly coefficient H1 remains statistically significant explanatory variable within long-only top decile portfolio of BE/ME, even after controlling returns with widely known risk-factors explaining cross section of stock returns (Fama and French, 1993; Carhart, 1997; Pastor and Stambaugh, 2003). This thesis also provides evidence that market-wide liquidity premium does not explain half-year anomaly in the overall U.S. stock market. Sub-period regressions show that half-year effect and month-of-the-year effect are persistent within value anomaly in U.S. stock market. Furthermore, GARCH (1,1) model reveals that lagged value of variance and lagged squared error term have statistically significant effect on future expected returns in each factor portfolio, thus returns exhibit time varying risk premium, which may to some extent explain seasonal nature of stock returns within fundamental anomalies.

Reasons behind the results of this thesis are many. Limits to arbitrage and non-fundamental demand could partially explain the results. Risk aversion of investors during the summer months can also accumulate half-year effect within all factor portfolios as mentioned by Bouman and Jacobsen (2002). Persistent SIZE portfolio returns could be due to the leverage constraints faced by arbitrageurs, hard-to-arbitrage argument and benchmarking (Baker and Wurgler, 2007). Therefore, stock prices of small caps do not adjust as effectively as in larger capitalization companies because of the decline in demand toward high yield small capitalization companies. Superior performance of value anomaly within half-year anomaly in the long run could be partially stemming from information overload and representativeness heuristic nature of human behavior. Thereby, investors take actions only according to latest piece of news and make false assumption according to information, driving them into stocks which have momentum and hype around them, and therefore, companies with low valuation go under the radar. Thus the mispricing endures and is exploitable for investors. Even though risk-adjusted metrics of volatility, Sharpe and Adjusted Sharpe ratio do not exhaustively support the conclusion of the nested value anomaly returns being compensation for the inflated risk, we should consider this as one possible explanation. Cost reversibility and high countercyclical risk of assets in place could to a certain degree rise the riskiness of value anomalies (Zhang, 2005). Also, high level of BE/ME usually indicates low level of earnings and vice versa (Fama and French, 1995). With these notations, it would be interesting to examine whether the earnings growth spread between value versus growth strategies during the half-year anomaly period could account for value-minus growth strategies returns spread in the long run.

The results of the study are somewhat consistent with previous findings on fundamental anomalies and calendar anomalies (e.g., see Fama and French, 1992; Bouman and Jacobsen, 2002; Jacobsen, Mamun and Visaltanachoti, 2005). Portfolios used in this thesis are zero-cost portfolios. Hence future research could extend results to include costs associated with trading volume for example taxes, bid-ask spreads and other transaction costs. This way, more robust results and valid conclusions could be achieved especially for the portfolios with short holding periods. This thesis broadly utilizes behavioral framework, factor model and explanations found by previous researchers in reasoning deviations from market efficiency. One possible extension for this thesis could be inclusion APT model, thus systematic risk factors such as movements in interest rates, inflation levels, employment rates, purchasing manager indices, GDP growth rates and market sentiment for explaining results. This thesis also utilizes U.S. stock markets returns data and NYSE, Nasdaq and Amex as market index. Therefore, naturally different markets and benchmark index could be a topic for further research. Marrett and Worthington (2011) found out, that January effect was thirty-three times higher in telecommunication industry compared to other industries. With this in mind, significant extension for this thesis would be to investigate different industries and nested anomalies within them. Structure of company's balance sheet plays also somewhat important role in overall company analysis and therefore research of this thesis could also be extended to include portfolio formation criteria that takes this into account, for example EV/EBITDA or F-score.

Application of the results within stock markets and beyond them should be done with caution. However, the results of this thesis can be considered along with other criteria and previous research results, when building an investment portfolio. Although, there is statistically significant difference in returns between half-year anomaly period and rest of the year within fundamental anomalies, especially in the case of value portfolios, one must remember, that results are observations from the past. There is no guarantee that same patterns will repeat themselves in the future. However, the best indicator of future and to be more specific the only indicator of future we have is, conveniently, the past.

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APPENDIX

Appendix 1. Sharpe ratio and Adjusted Sharpe ratio for month-of-the-year long and long-short decile portfolios trading anomalies.

In this table Sharpe ratio is first number and number below is Adjusted Sharpe ratio (bolded) for each month-of-the-year decile portfolio. Sharpe Ratios are calculated without risk-free instrument during out-of-the-market periods. If mean return over some specific month has been negative, in order to avoid any biases in interpretation, excess return measure is multiplied instead of divided with volatility. Figures are annualized with best practice possible.

LONG	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
SIZE	2,447	0,732	0,826	0,461	0,228	0,253	-0,008	-0,012	0,06	-0,048	0,342	0,632
	4,588	***0,792***	***0,611***	***0,437***	***0,229***	***0,257***	***-0,008***	***-0,012***	***0,06***	***-0,049***	***0,33***	***0,664***
BE/ME	1,428	0,753	1,179	1,086	0,06	0	0,136	0,092	-0,025	-0,02	0,817	1,279
	1,405	***0,763***	***0,947***	***1,035***	***0,06***	***0***	***0,135***	***0,091***	***-0,025***	***-0,02***	***0,859***	***1,34***
OP	0,72	0,254	0,749	0,969	0,414	0,2	0,168	0,085	-0,007	0,371	1,116	1,023
	0,786	***0,257***	***0,665***	***0,994***	***0,415***	***0,199***	***0,168***	***0,084***	***-0,007***	***0,337***	***1,092***	***1,164***
E/P	1,168	0,682	1,243	1,4	0,255	0,013	0,408	0,085	-0,003	-0,01	0,931	1,334
	1,41	***0,72***	***1,405***	***1,77***	***0,257***	***0,013***	***0,416***	***0,084***	***-0,003***	***-0,01***	***0,868***	***1,529***
CFP	1,212	0,622	1,259	1,643	0,27	0,029	0,113	0,22	-0,002	-0,013	0,726	1,246
	1,486	***0,615***	***1,19***	***2,133***	***0,268***	***0,029***	***0,112***	***0,214***	***-0,002***	***-0,013***	***0,717***	***1,063***
D/P	0,854	-0,007	0,896	1,127	0,152	-0,002	0,607	0,985	0,224	0,132	0,305	0,633
	0,586	***-0,007***	***1,023***	***1,164***	***0,155***	***-0,002***	***0,652***	***1,135***	***0,22***	***0,128***	***0,276***	***0,665***
MOM	0,705	0,881	1	0,949	0,622	0,709	0,051	0,27	0,182	0,101	1,115	1,396

	0,752	***0,975***	***0,467***	***1,049***	***0,624***	***0,698***	***0,051***	***0,27***	***0,179***	***0,1***	***0,801***	***1,773***
ACC	1,068	0,43	0,725	0,831	0,097	0,059	0,291	0,174	0,04	-0,001	0,983	1,15
	1,234	***0,429***	***0,696***	***0,841***	***0,097***	***0,059***	***0,292***	***0,171***	***0,04***	***-0,001***	***0,868***	***1,304***
BETA	0,456	0,118	0,938	1,548	0,603	0,144	0,383	0,34	-0,002	0,762	0,857	1,209
	0,468	***0,118***	***0,893***	***1,006***	***0,637***	***0,142***	***0,389***	***0,332***	***-0,002***	***0,727***	***0,85***	***1,335***
NETISS	0,605	0,453	1,054	1,004	0,128	-0,002	0,021	0,21	-0,006	0,449	0,792	1,336
	0,649	***0,442***	***1,069***	***1,147***	***0,128***	***-0,002***	***0,021***	***0,208***	***-0,006***	***0,407***	***0,722***	***1,628***
VAR	0,383	0,114	1,125	1,048	0,228	0,025	0,327	0,461	0,181	0,484	1,041	1,085
	0,4	***0,114***	***1,302***	***0,982***	***0,228***	***0,025***	***0,328***	***0,459***	***0,178***	***0,448***	***1,018***	***1,108***

LONG SHORT	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
SIZE	2,534	0,586	0,067	-0,016	-0,003	0,029	-0,017	-0,014	0,262	-0,053	-0,017	-0,006
	4,897	***0,631***	***0,066***	***-0,016***	***-0,003***	***0,029***	***-0,017***	***-0,014***	***0,264***	***-0,053***	***-0,017***	***-0,006***
BE/ME	1,332	0,433	0,533	0,346	-0,011	-0,008	-0,003	-0,006	-0,012	-0,04	-0,007	0,486
	1,277	***0,463***	***0,551***	***0,377***	***-0,011***	***-0,008***	***-0,003***	***-0,006***	***-0,012***	***-0,04***	***-0,007***	***0,506***
OP	-0,036	-0,011	-0,006	0,021	0,38	0,158	0,69	-0,005	-0,002	1,017	-0,001	-0,01
	-0,036	***-0,011***	***-0,006***	***0,021***	***0,391***	***0,157***	***0,759***	***-0,005***	***-0,002***	***1,177***	***-0,001***	***-0,01***
E/P	0,6	0,331	0,341	0,325	-0,009	-0,009	0,275	-0,006	0,369	-0,03	-0,014	0,406
	0,639	***0,328***	***0,357***	***0,336***	***-0,009***	***-0,009***	***0,28***	***-0,006***	***0,387***	***-0,03***	***-0,014***	***0,413***
CFP	0,74	0,203	0,41	0,572	-0,009	-0,007	0,037	-0,004	0,303	-0,029	-0,016	0,339
	0,828	***0,205***	***0,423***	***0,608***	***-0,009***	***-0,007***	***0,037***	***-0,004***	***0,311***	***-0,029***	***-0,016***	***0,344***
D/P	0,129	-0,024	-0,006	-0,005	-0,013	-0,008	0,277	0,594	0,691	-0,011	-0,045	-0,019
	0,128	***-0,024***	***-0,006***	***-0,005***	***-0,013***	***-0,009***	***0,285***	***0,655***	***0,792***	***-0,011***	***-0,045***	***-0,019***
MOM	-0,080	0,986	0,042	-0,031	0,680	1,458	0,499	0,011	1,126	0,615	0,799	1,356
	-0,082	***1,221***	***0,041***	***-0,031***	***0,632***	***1,772***	***0,487***	***0,011***	***0,969***	***0,610***	***0,744***	***1,772***
ACC	0,448	-0,004	-0,001	-0,002	-0,004	0,074	1,057	-0,002	0,917	0,42	-0,003	0,298
	0,476	***-0,004***	***-0,001***	***-0,002***	***-0,004***	***0,075***	***0,922***	***-0,002***	***1,058***	***0,448***	***-0,003***	***0,32***
BETA	-0,119	-0,022	-0,014	-0,003	0,131	0,498	0,221	-0,018	0,264	0,49	-0,051	-0,013
	-0,12	***-0,022***	***-0,014***	***-0,003***	***0,131***	***0,508***	***0,216***	***-0,018***	***0,266***	***0,509***	***-0,051***	***-0,013***
NETISS	-0,015	0,121	0,609	0,107	-0,006	0	0,44	0,218	0,141	0,6	0	0,356
	-0,015	***0,121***	***0,669***	***0,109***	***-0,006***	***0***	***0,439***	***0,223***	***0,139***	***0,623***	***0***	***0,376***
VAR	-0,121	0,001	0,05	-0,012	0,251	0,301	0,707	0,164	0,398	0,874	-0,029	0,101
	-0,122	***0,001***	***0,05***	***-0,012***	***0,243***	***0,285***	***0,664***	***0,166***	***0,413***	***0,931***	***-0,029***	***0,099***

Appendix 2. Descriptive statistics of deciles of each portfolio.

Data obtained from Kenneth French data library.

	SIZE	BE/ME	OP	E/P	CF/P	D/P	ACC	BETA	ISS	VAR	MOM
	Lo 10	Lo 10	Lo 10	Lo 10	Lo 10	Lo 10	Lo 10	Lo 10	Lo 10	Lo 10	Lo 10
Mean	0,011	0,009	0,007	0,009	0,009	0,009	0,012	0,009	0,01	0,009	0,002
σ	0,062	0,05	0,064	0,056	0,055	0,056	0,056	0,034	0,043	0,033	0,080
σ^2	0,004	0,003	0,004	0,003	0,003	0,003	0,003	0,001	0,002	0,001	0,006
Kurt.	2,446	1,53	1,805	1,488	1,501	1,921	1,603	1,976	2,282	1,251	4,126
Skew.	-0,148	-0,242	-0,586	-0,243	-0,37	-0,441	-0,359	-0,288	-0,442	-0,293	0,582
Range	0,585	0,458	0,496	0,486	0,491	0,499	0,455	0,317	0,374	0,265	0,716
Min	-0,289	-0,227	-0,323	-0,259	-0,26	-0,269	-0,251	-0,131	-0,206	-0,14	-0,261
Max	0,295	0,23	0,173	0,227	0,231	0,23	0,204	0,187	0,168	0,125	0,455
n	675	675	675	675	675	675	675	675	675	675	675
	Hi 10	Hi 10	Hi 10	Hi 10	Hi 10	Hi 10	Hi 10	Hi 10	Hi 10	Hi 10	Hi 10
Mean	0,009	0,012	0,01	0,012	0,012	0,01	0,007	0,01	0,005	0,004	0,015
σ	0,042	0,061	0,045	0,052	0,052	0,044	0,058	0,078	0,056	0,087	0,061
σ^2	0,002	0,004	0,002	0,003	0,003	0,002	0,003	0,006	0,003	0,008	0,004
Kurt.	1,755	3,998	2,131	2,388	2,334	7,188	1,85	1,141	1,631	1,683	1,906
Skew.	-0,356	-0,142	-0,444	-0,319	-0,356	-0,407	-0,503	-0,215	-0,414	-0,069	-0,402
Range	0,378	0,612	0,407	0,483	0,489	0,575	0,481	0,666	0,476	0,68	0,498
Min	-0,197	-0,264	-0,247	-0,223	-0,228	-0,291	-0,289	-0,331	-0,26	-0,341	-0,267
Max	0,181	0,348	0,16	0,261	0,261	0,283	0,192	0,335	0,216	0,339	0,231
n	675	675	675	675	675	675	675	675	675	675	675

Appendix 3. Period 1 month-of-the-year regressions for long portfolios.

Data used in regressions consist of U.S. securities data 1963 and 2019. Period 1 consist of portfolio returns between July 1963 and December 1990 (N=330). P-values in parentheses. Regressions use Newey-West corrected standard errors (lag=3). Statistically significant values are bolded and marked with asterisks when considered important. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

Period 1

Long	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
SIZE	**.0543074***** (0.000)	.0108741	.0064704	.0016963	-.0015778	-.004263	-.0000929	-.0097321	.0055071	**-.0223429***** (0.005)	-.0113429* (0.089)	-.0034107
BE/ME	**.0393074***** (0.000)	.012237* (0.061)	.0068259	.0013222	-.0048593	-.0007593	.0048357	.00405	-.0006143	-.01095* (0.054)	-.0014071	.0036107
OP	-.0003889	-.0004593	.0001444	.0026778	.0019481	-.0000815	.0006214	-.0011679	-.0019286	.0025071	-.0001893	.0010429
E/P	**.027363***** (0.000)	.0037519	.0076037* (0.092)	.0022852	-.0012593	-.0008	.0065857* (0.055)	.0032857	.0032571	**-.0160321**** (0.018)	-.0028964	-.0009607
CF/P	**.0250593***** (0.001)	.0059111	.0074148* (0.069)	.0025704	.0020222	.0000111	.0050571	.0073321* (0.076)	.0052643	-.0121429* (0.076)	-.0020893	.0014857
D/P	**.0232074***** (0.004)	-.0045926	-.0000667	-.004037	.0000185	.0008963	.0033	.0054036	.0057464	.0020357	-.0094929	-.0080464* (0.071)
MOM	-.0003889	.0097593	.0095* (0.073)	**.0155259***** (0.000)	.011137* (0.055)	.0088296	-.0014357	.0003857	.0072107	-.0010857	**.0205286***** (0.001)	.0073321
ACC	.0070519	.0057259	.0020074	.0026963	-.0002815	-.0001444	.0059429	-.0000393	.0043464	-.00905	.0063321	.0021429
BETA	-.0019667	-.0024852	-.0019037	-.0027444	.0057667	.0021593	.00455	-.0028214	.0026107	**.0132071**** (0.025)	-.0035571	-.0012714
ISS	**-.0040963**** (0.040)	.0057481	.0009963	-.0004444	-.002437	-.002037	-.0024393	-.001375	-.0018857	.0023393	-.0013571	.0037571* (0.097)
VAR	-.0016	-.0035407	-.0019889	-.0038407	.0002778	.0011519	.0009536	-.0018464	.0049214	.0049214	-.0019643	-.0009607

Appendix 4. Period 2 month-of-the-year regressions for long portfolios.

Data used in regressions consist of U.S. securities data 1963 and 2019. Period 2 consist of portfolio returns between January 1991 and September 2019 (N=345). P-values in parentheses. Regressions use Newey-West corrected standard errors (lag=3). Statistically significant values are bolded and marked with asterisks when considered important. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

Period 2

Long	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
SIZE	**.028969***** (0.003)	.0089483	.0006862	-.0077069	.0054552	.011131	-.0097414	-.0027759	.0062448	**-.0171143***** (0.003)	-.002125	-.0005179
BE/ME	.0074138	.0040172	**.0115931**** (0.045)	.0143345	.0025034	-.0003172	-.0039586	-.0025828	-.0099138* (0.091)	-.0110821	.0044643	.0093143* (0.072)
OP	.0009069	-.0002138	-.0006897	-.0012138	.0034586	.0034345	.0004034	.0011172	.003931	.0018786	.0042643	-.0018036
E/P	-.0015828	.0073897	**.0081655**** (0.033)	**.0098276**** (0.040)	.0040345	.0004828	.0013483	-.0027069	.0040655	-.000325	.0039321	.0101286* (0.077)
CF/P	.0017517	.0040517	**.0095621**** (0.044)	**.0155276***** (0.008)	.0011552	.0001517	-.005069	-.0020655	.0026	-.0066643	-.0023786	.0067357
D/P	-.0118069	-.0102034	.0040138	.0057483	-.0001069	-.0033276	.0074966	.0154448* (0.067)	.0089448	-.0079214	-.0084321	-.0011714
MOM	.0065103	.0124276	.0026897	-.0084862	.0053586	.0109034* (0.074)	-.0000241	.006931	.0090552	-.003275	-.0038679	.0126071* (0.082)
ACC	.0104931* (0.058)	-.0002517	.0018655	-.0004655	-.0005828	.0009069	-.0002207	.0035966	.0066862	-.0007036	.0053536	.0042286
BETA	-.0109793* (0.069)	-.0019414	.0011	.0033414	.0006828	.0000759	-.0002069	.0080862	.0048414	-.0017214	-.0064036	-.0020286
ISS	-.0024448	-.0004517	.007	-.002069	.0013103	-.0017552	-.0002172	.0043034	.0051241	.0041214	-.0052	.0026357
VAR	**-.0125276**** (0.046)	-.001069	.0014276	-.0012207	-.0001621	-.0012379	.0020793	.0089103	.0080724	-.0023429	-.0041857	-.0039643

Appendix 5. Period 1 month-of-the-year regressions for long-short factor portfolios.

Data used in regressions consist of U.S. securities data 1963 and 2019. Period 1 consist of portfolio returns between July 1963 and December 1990 (N=330). P-values in parentheses. Regressions use Newey-West corrected standard errors (lag=3). Statistically significant values are bolded and marked with asterisks when considered important. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

Period 1

Long-short	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
SIZE	**.038037*****	.0063593	-.0026815	-.0128519*	-.0054333	-.012037*	-.0013357	-.0219286*	.0105714	**-.0321786****	**-.0261929****	-.0157214*
	(0.007)			(0.092)		(0.071)		(0.077)		(0.026)	(0.019)	(0.098)
BE/ME	.0280444*	.008163	-.0038	-.0135222	-.0122778	-.0070852	.0069964	-.0044786	.0095821	-.0214143	-.0195179	-.0099214
	(0.068)											
OP	**-.0470111*****	-.0141963	-.0149037	-.0095889	.0082704	-.0008778	.0064464	-.0087643	.0033929	.0161786	**-.0207179****	-.0149
	(0.000)										(0.038)	
E/P	.0149407	-.0003259	-.0036037	-.0131222	-.0095519	-.0049037	.0118857	-.0088214	.0144429	-.022075	**-.0286821****	-.0113286
											(0.025)	
CF/P	.0128889	.0002074	-.005637	-.0116333	-.0059296	-.0064481	.0117821	-.0039964	.0152036	-.0163714	**-.0271607****	-.0092964
											(0.031)	
D/P	.0094704	-.0154148	-.0133185	-.0218926	-.0113259	-.010237	.0081929	-.0054714	.0144179	.002075	**-.0369393****	**-.0223571****
											(0.043)	(0.043)
MOM	**-.0417704****	.0126148	.0034667	.0175037	**.0242111****	.0160889	.0075964	-.0110607	.017425	.0213429	.0198714	.0074571
	(0.048)				(0.025)							
ACC	-.0171333	-.0018889	-.0082074	-.0116519	-.0035741	-.0022259	.0149071	-.0120393	.0118679	-.0042143	-.015375	-.0089964
BETA	**-.0530444****	-.0123963	-.0176704	-.0106556	.0082556	.0091296	.0091321	-.0222857	.0109643	.0291	-.0283571	-.0166679
	(0.049)											
ISS	**-.0318074****	.0015296	-.0029259	-.0088296	-.0026333	-.0024	.0024	-.0114179	.0047143	.0062357	-.0193143	-.0071964
	(0.049)											
VAR	**-.0527333****	-.0116074	-.0053667	-.0080111	.0108037	.0102037	.0142714	-.005975	.0159321	.0365429	-.0172464	-.0051
	(0.034)											

Appendix 6. Period 2 month-of-the-year regressions for long-short factor portfolios.

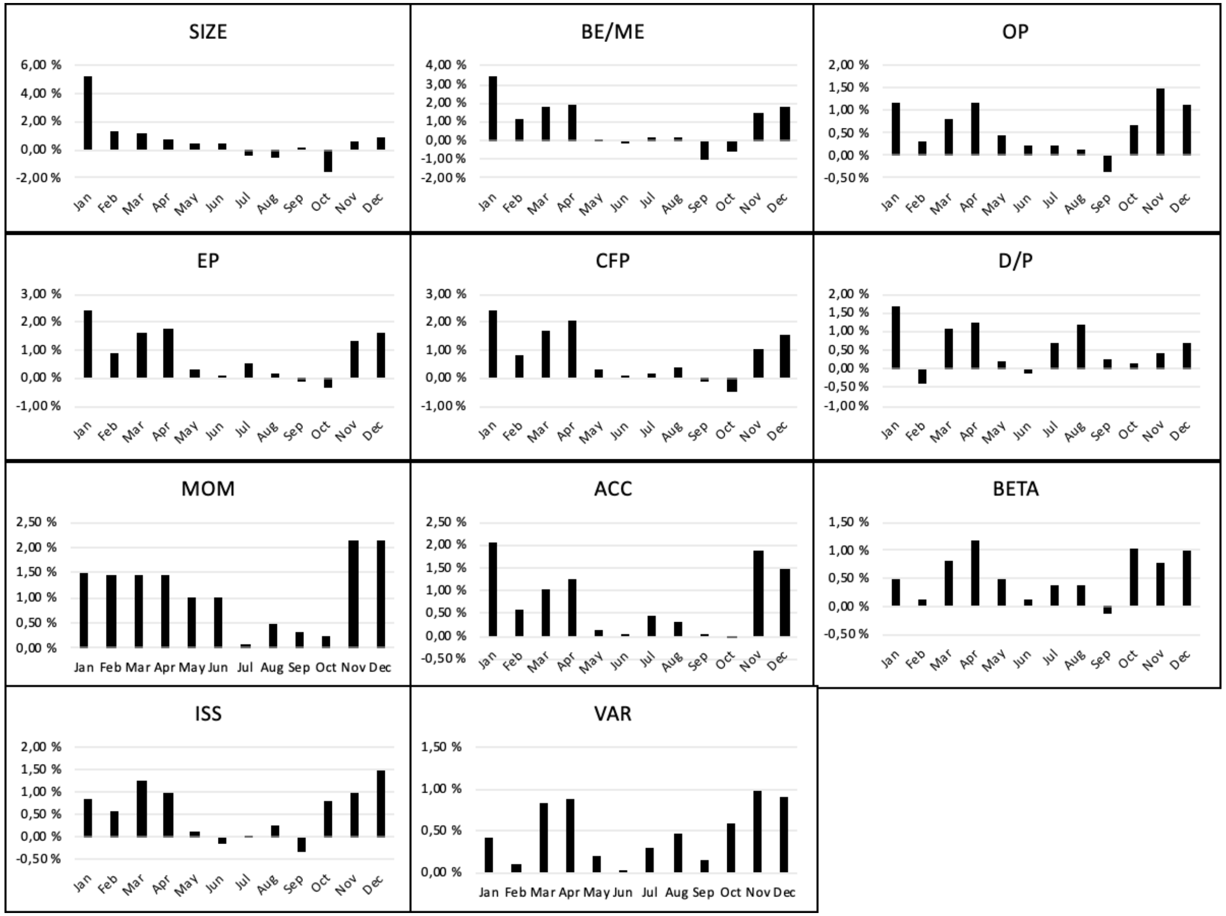
Data used in regressions consist of U.S. securities data 1963 and 2019. Period 2 consist of portfolio returns between January 1991 and September 2019 (N=345). P-values in parentheses. Regressions use Newey-West corrected standard errors (lag=3). Statistically significant values are bolded and marked with asterisks when considered important. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.)

Period 2

Long-short	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
SIZE	.0227862* (0.081)	.0057724	-.0123621	**-.0254759**** (0.024)	-.0016517	.0113207	**-.0226034**** (0.011)	.0004448	.0048828	**-.0339536***** (0.003)	-.0183714* (0.080)	-.0142214
BE/ME	-.0008552	-.0018759	-.0009724	.0004724	-.0063172	-.0041966	-.0136828	-.0042552	-.013869	**-.0267714**** (0.038)	-.013	-.0016214
OP	-.0160069	-.0045828	-.0103759	-.0125103	-.0041966	.0032172	.0061172	-.000531	.0038517	-.0006179	-.0061	-.0203429
E/P	-.0171241	.0026517	-.0071448	-.0031862	-.0072103	-.0064276	-.0085069	-.0038034	.0038	-.0145179	-.0115214	-.0019714
CF/P	-.0114414	-.0011034	-.0033793	.0012552	-.0115172	-.0030069	-.0136483	-.0042552	.0020448	-.0206071	-.0172107	-.0053536
D/P	-.0260138	-.0153897	-.0107897	-.0066897	-.0069862	-.0010414	-.0029103	.0199103	.0151586	-.0195964	-.0270464	-.0197143
MOM	-.0233966	.0183517	-.0180724	**-.0542414**** (0.030)	-.0008483	**.0313655**** (0.029)	.0059345	.0087828	.0293379* (0.076)	-.0076786	-.0149071	.0178107
ACC	.0024207	-.0133552	-.0106069	-.0136828	-.0084724	.0024966	-.0012379	.0047862	.0111759	.003875	**-.0171536**** (0.028)	-.0096929
BETA	-.0400586* (0.050)	-.0098241	-.0137138	-.0146621	-.007469	.0032379	-.0038034	.0057621	.0097345	-.01685	-.0305893	-.0185536
ISS	-.0147138	-.0052793	-.0030138	-.0115414	-.0109586	.0011897	.0036517	.0122793	.0076	-.0047679	-.006975	-.0107964
VAR	-.0399103* (0.069)	.0044345	-.0094655	-.0208448	-.0046069	.0010138	.0080483	.0095793	.0111414	-.0051607	-.0230036	-.0143107

Appendix 7. Monthly dispersion of portfolio returns.

Mean returns of each month within fundamental anomalies. Data used consist of U.S. securities returns' data from 1963 and 2019. Pre-calculated factor portfolios obtained from Kenneth French data library.



Appendix 8. Dickey-Fuller Test.

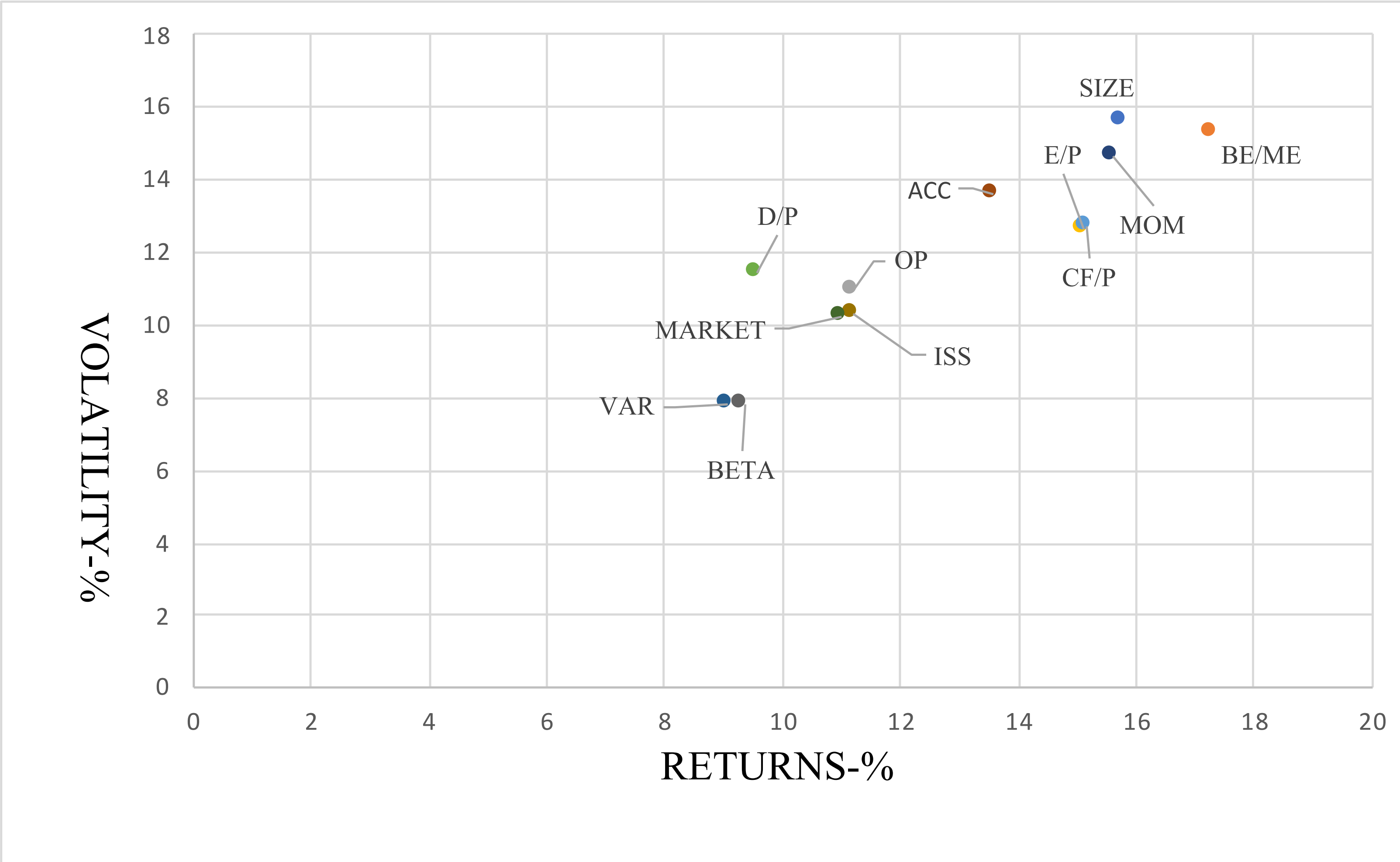
Test is conducted on every portfolios' return data. Data used consist of U.S. securities returns data from 1963 and 2019. (*, **, *** denote statistical significance at levels of 1%, 5% and 10% respectively.)

		INTERPOLATED DICKEY-FULLER TEST		
Critical Value	1 %	5 %	10 %	
	-3.430	**-2.860**	**-2.570**	

LONG	Z(t)	**LONG-SHORT**	Z(t)
SIZE	-20.550***	**SIZE**	-21.896***
BE/ME	-24.064***	**BE/ME**	-21.801***
OP	-22.768***	**OP**	-21.890***
E/P	-24.201***	**E/P**	-25.035***
CF/P	-24.156***	**CF/P**	-24.756***
D/P	-23.726***	**D/P**	-23.911***
MOM	-24.844***	**MOM**	-24.997***
ACC	-24.025***	**ACC**	-24.622***
BETA	-25.809***	**BETA**	-22.909***
ISS	-24.045***	**ISS**	-22.715***
VAR	-24.516***	**VAR**	-23.219***

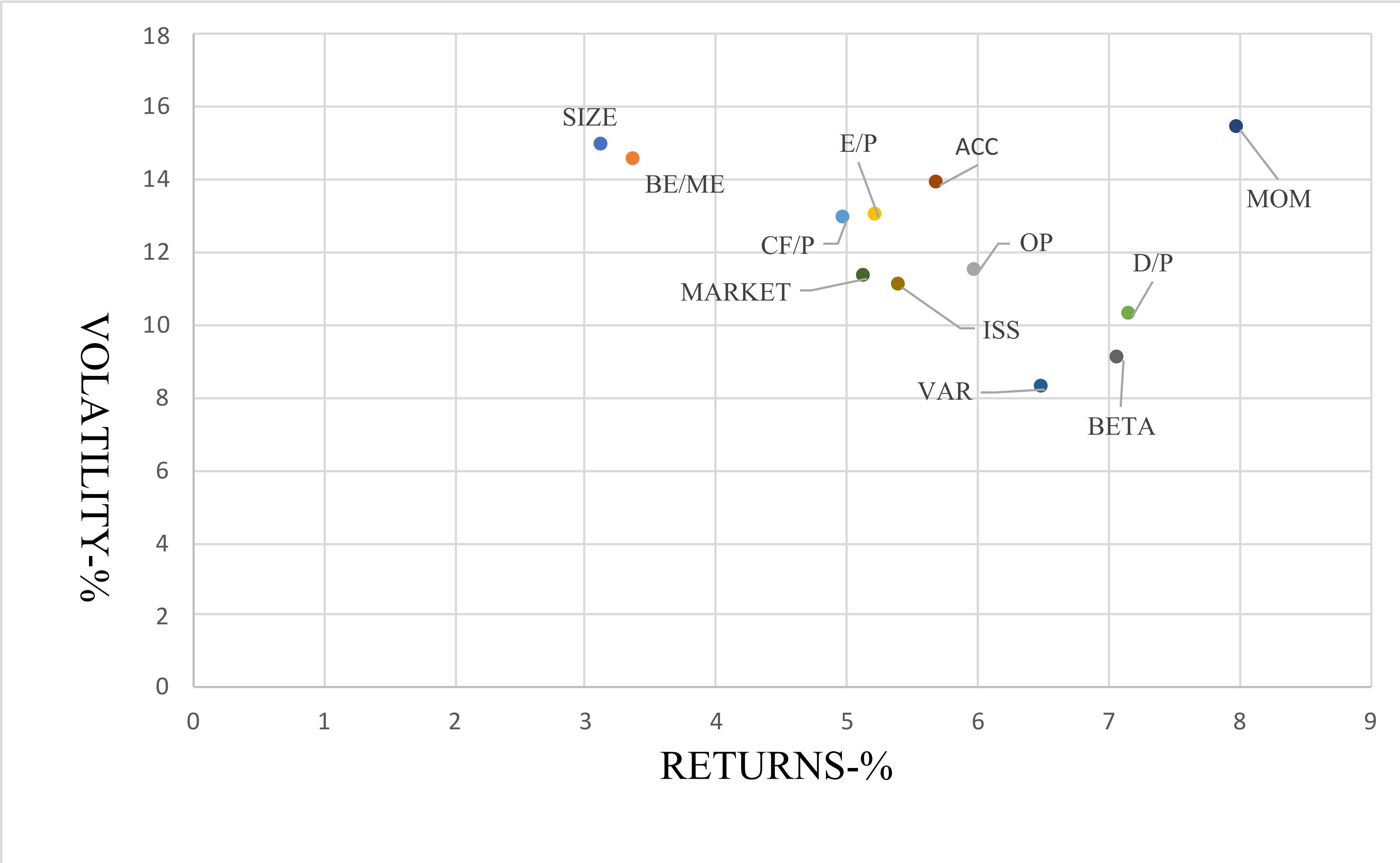
Appendix 9. Risk-Return scatter-plot for H1 long portfolios.

Figures in plot are annualized mean return and annualized volatility. In each factor portfolio, out-of-the-market periods are fully invested in 1-month U.S. treasury bill.



Appendix 10. Risk-Return scatter-plot for H2 long portfolios.

Figures in plot are annualized mean return and annualized volatility. In each factor portfolio, out-of-the-market periods are fully invested in 1-month U.S. treasury bill.



Appendix 11. Regression results of month-of-the-year anomaly within long-only top decile portfolios.

P-value of each regression is in parenthesis below. The dependent variable in each regression is the excess return over the market portfolio return whereas the independent variable is dummy variable of each month. Number of observations is 675 with each regression. Regressions use Newey-West HAC corrected standard errors with lag m = 3. Statistically significant values are bolded and marked with asterisks when considered important. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.

Long	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
SIZE	**0,0412***** (0.000)	0,010	0,003	-0,003	0,002	0,004	-0,005	-0,006	0,006	**-0,0197***** (0.000)	-0,007	-0,002
BE/ME	**0,0228***** (0.001)	0,008	**0,009**** (0.017)	0,008	-0,001	-0,001	0,000	0,001	-0,005	**-0,011**** (0.018)	0,002	0,006* (0.077)
OP	0,000	0,000	0,000	0,001	0,003	0,002	0,001	0,000	0,001	0,002	0,002	0,000
E/P	**0,0123**** (0.010)	0,006	**0,0079***** (0.007)	**0,0062**** (0.047)	0,001	0,000	0,004	0,000	0,004	-0,008* (0.077)	0,001	0,005
CF/P	**0,013***** (0.006)	0,005	**0,009***** (0.006)	**0,009**** (0.011)	0,002	0,000	0,000	0,003	0,004	**-0,009**** (0.030)	-0,002	0,004
D/P	0,005	-0,007	0,002	**0,001**** (0.015)	0,000	-0,001	0,005	**0,0105**** (0.036)	0,007* (0.050)	-0,003	-0,009	-0,005
MOM	0,003	**0,011**** (0.038)	0,0059* (0.091)	0,003	**0,008**** (0.038)	**0,001**** (0.016)	-0,001	0,004	**0,008**** (0.049)	-0,002	0,008	**0,001**** (0.023)
ACC	**0,009**** (0.025)	0,003	0,002	0,001	0,000	0,000	0,003	0,002	0,0055* (0.086)	-0,005	0,006	0,003
BETA	-0,007	-0,002	0,000	0,000	0,003	0,001	0,002	0,003	0,004	0,006	-0,005	-0,002
ISS	-0,003	0,003	0,004	-0,001	0,000	-0,002	-0,001	0,002	0,002	0,003	-0,003	0,003
VAR	**-0,046***** (0.005)	-0,003	-0,007	-0,015	0,003	0,005	0,011	0,002	0,013	0,016	-0,020	-0,010

Appendix 12. Regression results of month-of-the-year anomaly within long-short factor portfolios.

P-value of each regression is in parenthesis below. The dependent variable in each regression is the excess return over the market portfolio return whereas the independent variable is dummy variable of each month. Number of observations is 675 with each regression. Regressions use Newey-West HAC corrected standard errors with lag m = 3. Statistically significant values are bolded and marked with asterisks when considered important. (*, **, *** denote statistical significance at levels of 10%, 5% and 1% respectively.

Long-short	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
SIZE	**0,03***** (0.002)	0,006	-0,008	**-0,019***** (0.005)	-0,003	0,000	-0,012* (0.079)	-0,011	0,008	**-0,033***** (0.000)	**-0,022***** (0.003)	**-0,015**** (0.035)
BE/ME	**0,023***** (0.001)	0,008	**0,009**** (0.017)	0,008	-0,001	-0,001	0,000	0,001	-0,005	**-0,011**** (0.018)	0,002	0,006* (0.077)
OP	**-0,031***** (0.002)	-0,009	-0,013	-0,011	0,002	0,001	0,006	-0,005	0,004	0,008	-0,013	**-0,0176**** (0.027)
EP	-0,002	0,001	-0,005	-0,008	-0,008	-0,006	0,002	-0,006	0,009	-0,018	**-0,02**** (0.031)	-0,007
CFP	0,000	0,000	-0,004	-0,005	-0,009	-0,005	-0,001	-0,004	0,009	-0,018	**-0,022**** (0.011)	-0,007
D/P	-0,009	-0,015	-0,012	-0,014	-0,009	-0,005	0,003	0,007	0,015	-0,009	**-0,032***** (0.005)	-0,021
MOM	**-0,032**** (0.030)	0,016	-0,008	-0,020	0,011	**0,024**** (0.014)	0,007	-0,001	**0,0235**** (0.031)	0,007	0,002	0,013
ACC	-0,007	-0,008	-0,009	-0,0127* (0.062)	-0,006	0,000	0,007	-0,003	0,012	0,000	**-0,016**** (0.012)	-0,009
BETA	**-0,046***** (0.005)	-0,011	-0,016	-0,013	0,000	0,006	0,003	-0,008	0,010	0,006	**-0,029**** (0.048)	-0,018
ISS	**-0,023**** (0.015)	-0,002	-0,003	-0,010	-0,007	-0,001	0,003	0,001	0,006	0,001	-0,013	-0,009
VAR	**-0,046***** (0.005)	-0,003	-0,007	-0,015	0,003	0,005	0,011	0,002	0,013	0,016	-0,020	-0,010