Aalto University
School of Business

QUARTERLY SEASONALITY IN U.S. STOCK RETURNS

Master's Thesis
Eero Sormunen
Aalto University School of Business
Finance
Spring 2018

Aalto University
School of Business

Aalto University, P.O. BOX 11000, 00076 AALTO
www.aalto.fi

Abstract of master's thesis

Author Eero Sormunen	
Title of thesis Quarterly Seasonality in U.S. Stock Returns	
Degree Master of Science in Finance	
Degree programme Finance	
Thesis advisor(s) Peter Nyberg	
Year of approval 2018	**Number of pages** 63	**Language** English

Abstract

This Thesis proves a quarterly seasonality pattern in U.S. stock returns: stock's expected return in a given month *t* is correlated with its returns in past lagged quarterend months i.e. months *t-3,6,9,...*. Strategies based on quarterend lags outperform those based on past returns of all months. Unlike in the case past returns in general, the correlation between the stock price and quarterend lags does not reverse after the most recent past year. Indeed, the quarterend lags do not seem to contribute to long-term return reversal phenomena.

The return pattern is strong. A zero-investment strategy investing based on the returns of the past four quarterends yields on average 1.25% per month in the period of 1946-2016 and is both more profitable and less risky than a traditional momentum portfolio during the same period. Returns of zero-investment quarterend portfolios are significantly positive in all tested formation intervals up to lagged 20 years.

Quarterly seasonality cannot be solely explained by the annual seasonality found by Heston and Sadka (2008) but portfolios based on nonannual quarterend lags still yield higher returns than other strategies. The quarterend pattern is stronger in value weighted returns but also exists in equal weighted portfolios. Controlling for firm-specific events of the calendar year like earnings announcements and ex-dividend dates does not diminish the superiority of quarterend strategies, nor are their returns tied to any particular calendar period of the year.

Keywords momentum, effect of past returns, cross-sectional seasonality, quarterly seasonality

Aalto-yliopisto
Kauppakorkeakoulu

Aalto-yliopisto, PL 11000, 00076 AALTO
www.aalto.fi

Maisterintutkinnon tutkielman tiivistelmä

Tekijä Eero Sormunen	
Työn nimi Quarterly Seasonality in U.S. Stock Returns	
Tutkinto Kauppatieteiden maisteri	
Koulutusohjelma Rahoitus	
Työn ohjaaja(t) Peter Nyberg	
Hyväksymisvuosi 2018	**Sivumäärä** 63 **Kieli** englanti

Tiivistelmä

Tässä maisterintutkinnon tutkielmassa on todistettu, että yhdysvaltalaisosakkeiden odotettu tuotto annetulla kuukaudella *t* on riippuvainen sen tuotoista menneinä neljännesvuosina, eli kuukausina *t-3,6,9,...*. Strategiat, jotka perustuvat menneiden neljännesvuosien tuottoihin, tuottavat paremmin kuin kaikkiin menneisiin kuukausituottoihin perustuvat strategiat. Toisin kuin menneisiin tuottoihin perustuvat strategiat yleensä, korrelaatio osakkeen hinnan ja menneiden neljännesvuosien tuottojen välillä ei muutu käänteiseksi yhden vuoden jälkeen.

Löydetty kaavamaisuus on vahva. Markkinaneutraali portfolio, joka myy lyhyeksi yhtä paljon kuin sijoittaa, ja on rakennettu viimeisimpien neljän menneen neljännesvuoden tuottojen perusteella tuottaa keskimäärin 1,25% kuukaudessa ajanjaksolla 1946-2016. Portfolio on sekä tuottavampi, että vähäriskisempi kuin perinteinen momentum-portfolio, joka perustuu kuukausiin *t-2:12*. Markkinaneutraaleiden menneisiin neljännesvuosiin perustuvien portfolioiden tuotot ovat merkitsevästi positiivisia kaikilla testatuilla portfolion rakennusaikaväleillä jopa 20 vuoteen saakka.

Kaavamaisuutta ei voi täysin selittää osakkeiden odotettujen kalenterikuukausituottojen eroilla, jonka löysivät Heston ja Sadka (2008). Portfoliot, jotka perustuvat muihin kuin vuosittaisiin menneisiin neljännesvuosiin voittivat yhä muut strategiat. Neljännesvuosittainen kaava on voimakkaampi markkina-arvopainotetuissa strategioissa, mutta näkyy myös niissä strategioissa, joissa joka osakkeelle on annettu sama paino. Yrityskohtaisten tapahtumien, kuten tulosjulkistusten tai osingon irtoamispäivän kontrollointi ei poista neljännesvuosistrategioiden ylivertaisuutta. Strategioiden tuotto ei myöskään ole rajattu mihinkään tiettyyn kalenterikuukauteen tai vuodenaikaan.

Avainsanat momentum-ilmiö, kausiluontoiset tuotot, neljännesvuosittainen kausittaisuus

Table of Content

List of Figures and Tables

1. Introduction

The momentum effect, or the tendency of past winners to outperform past losers in the stock market, is one of, if not the most prominent anomaly left unexplained by the Capital Asset Pricing Model (CAPM) by Sharpe (1964). The phenomenon was found by Jegadeesh and Titman who in their 1993 article showed that significant abnormal returns were to be earned when investing stocks based on their performance of last three to twelve months. Momentum has since been proved to affect multiple major asset classes beyond listed equities (e.g. Kho (1996) and Erb and Harvey (2006) and also to be present in markets outside U.S. (Rouwenhorst (1998,1999). Despite of the full 25 research filled years from its birth, the momentum effect continues to puzzle the academia.

Besides their dependence of past returns, stock returns are known to follow certain seasonal patterns. Small stocks thrive in January (Sidney Wachtel (1942) and stock performance tends to peak at days preceding holidays (Lakonishok and Smidt (1988). Even further, time of month, week and trading day all hold an effect on expected returns (Ariel (1987), Cross (1973) and (Harris (1986). However, before more recent advancements in the field of finance, little research was put to cross-sectional seasonal differences in individual stocks and the effect on past returns beyond the intermediate horizon.

Heston and Sadka (2008) discovered that individual stock returns follow a seasonal pattern: Stocks' performance of a given calendar month correlates to its performance of the same calendar month up to 20 years in the future. This leads to a pattern in correlation repeating itself every 12 moths i.e. annually. The authors formed winners-minus-losers portfolios out of U.S. listed equities based on their performance on past annual lagged months and showed that significant abnormal returns were earned with the strategy. The seasonal pattern had economic significance and could not be explained by the three-factor model by Fama and French (1993), nor with liquidity of the security or with industry of the underlying company. Later in their 2010 paper Heston and Sadka proved this annual seasonality to also exists in international stock markets.

The seasonality literature was later extended by Keloharju, Linnainmaa and Nyberg (2016) who showed that rather than being a factor in itself, seasonalities were aggregated by securities across characteristics of different factors. They proved the annual cross-sectional pattern to extend to securities past listed common equity and also to several stock market anomalies. The authors found that seasonal winners-minus-losers strategies correlate weakly to each other and sustain considerably riskiness even when well diversified, implying systematic factors behind the phenomenon. Keloharju et al. exploited the seasonal tendencies found in anomalies to create an anomaly-portfolio-trading metastrategy with high abnormal returns. They noted, that the same-calendar-performance of anomalies was strong enough for future anomalies to be identified by solely studying variables accosiated with return seasonalities.

Several company-specific events have been found to have an effect to the stock price, as proven for example by Beaver (1968) and Hartzmark and Solomon (2013). Many of the said events are imbedded to the fiscal year of a publicly listed company, most notorious being quarterly earnings announcements and dividend issuances, both of which signal crucial information about the state of affairs of the firm to the markets (Aharony and Swary (1980). The firm-specific events of the fiscal also have a strong influence on the returns of the strategies based on past returns. In their original study of momentum in 1993, Jegadeesh and Titman noticed that the profits of the momentum portfolios were concentrated around earnings announcement dates. Heston and Sadka (2008) confirmed their findings, but noted that the effect of earnings announcement is considerably smaller in portfolios based on lagged returns beyond the most recent year.

In this Master's Thesis, I will concentrate on previously undiscovered pattern of quarterly seasonality of stock returns. I will show that alongside with annual cross-sectional seasonality, there exists a weaker but distinctive quarterly pattern: Stock's performance in given month *t* is dependent on its returns in past quarterend months i.e. months *t-3*, *t-6*, *t-9*,…. Strategies based on the returns of lagged quarterend months outperform those based on other past months. For example, a zero-investment portfolio based on the returns of last four quarterend lags earns average returns of 1.25% *monthly* from 1946 to 2016, while a portfolio based on non-quarterend lags yields on average 0.25% during the same period. Quarterend strategies outperform other strategies based on past returns in all investigated portfolio formation intervals and yield significantly positive returns up to portfolios based on 20-year lagged returns.

Quarterly seasonality cannot be solely explained by the strong annual seasonality phenomenon research by my predecessors. Zero-investment nonannual quarterend portfolios continue to outperform strategies based on all lagged months and earn positive, although mostly insignificant, average returns. This implies that past quarterend months do not seem to contribute to the long-term return reversal phenomena found by De Bondt and Thaler (1985). Quarterly seasonality exists in both value weighted and equal weighted portfolio returns and also in portfolios made exclusively out of companies of large market capitalization, implying that the phenomena is not tied to any particular size group. To find an underlying reason behind quarterly seasonality, the effect of firm-specific events like quarterly earnings announcements and ex-dividend dates is tested as is the calendar-month seasonality of the quarterend portfolio returns.

The effect of past quarterend months to traditional intermediate horizon momentum phenomenon is strong. Even after taking into account the short-term return reversal, it is more lucrative and less-risky to invest based on stock returns of past four quarters than based on all the months of traditional momentum strategy. The results of my Thesis can help us to better understand the cross-sectional seasonality and the effect of past returns to stock price. They bring new information about the long-term return reversal effect, as it curiously does not seem to affect to past quarterend months like it does to others. The strong correlation between the returns of lagged quarterend months and stock price may also have practical implementations in the asset management industry. Most importantly, my finding concerning the effect of quarterend months to momentum profits could bring new to the thoroughly research filed of past intermediary horizon returns.

The rest of my work is organized as follows: the next section will go through some of the most prominent previous studies related the effect of past returns, seasonality and firm-specific seasonal events. The Section 3 briefly covers my motivation for the topic and sets out the three hypotheses of this study. The Section 4 will describe the data and methodology used for the Thesis and Section 5 presents my results that are further discussed and compared to previous findings of the academia in Section 6. Section 7 concludes.

2. Literature Review

I will next go through previous academic research on the topic of this Thesis. First, I introduce papers significant to our understanding of the effect of past returns to stock price, focusing on the momentum phenomenon. Next, I will concentrate on the two key papers of the field of cross-sectional seasonality, both vital for my study. Lastly, I will forgo research on the stock price effect of firm-specific seasonal events and some studies about post-earnings-announcement-drift potentially important to the robustness checks of my work.

2.1.Effect of past returns to stock price

De Bondt and Thaler (1985) found that stocks that have performed poorly will outperform those excelled in last three to five years when using a holding period of same length. The effect was much more significant on past losers than on past winners and was concentrated on second and third year after the portfolio formation. They also noted that the portfolio of loser stocks earned high returns during the month of January. De Bondt and Thaler offered investor overreaction as an explanation for the phenomena. This effect, later named as long-term reversal, has been since research for example by Grinblatt and Moskowitz (2004) who found it at least partly independently evolved from the intermediate-term momentum.

Jegadeesh (1990) presented empirical evidence on the predictability of past monthly returns to stocks price. The most prominent finding was the strong negative correlation of the most recent past month, a phenomenon later named as short-term reversal effect. The effect was found on stocks of all size categories. Jegadeesh also found the existence of positive price correlation on longer lags, 12-month serial correlation being the strongest. Lags 24 and 36 were found significantly positive as well. To my knowledge, this was the first mention of the annual lags in the finance literature. Like De Bondt and Thaler, Jegadeesh found the month of January to effect significantly to correlations of past returns. The cause behind phenomena of short-term reversal has since been debated in the academia, one prominent explanation being overreaction (e.g. Subrahmanyam (2005).

Jegadeesh and Titman's 1993 study is credited as the birth of the traditional momentum anomaly. They formed winners-minus-losers portfolios based on stocks past performance with formation intervals of 3,6,9 and 12 months and holding periods of same lengths, consisting altogether 16 strategies. Returns of nearly all strategies were significantly positive, a strategy trading stocks based on their past 12-month returns and holding it for 3 months being the most profitable one. They chose a strategy with both 6-month formation and holding periods (6/6 portfolio) for further analysis and tested its exposure to firm size and stock beta, finding only small differences in the magnitude of returns. When investigating seasonal effects, the authors found their momentum portfolios to lose in January with considerably magnitude. This behaviour was traced back to poor performance of small companies in the portfolio.

When portfolio returns were observed up to 36 months from formation, part of the abnormal returns were noticed to absolve after the intermediate period of first year. The authors noted the short-term reversal effect to be affecting the returns of the first month after formation. Jegadeesh and Titman also found that winners-minus-losers strategies performed particularly well around earnings announcement dates in the next seven months after the portfolio formation. These returns consisted approximately 25% of the winners-minus-losers 6/6 portfolio's returns. Also, this pattern was found to reverse after longer periods, losers outperforming winners in times of announcements.

The momentum phenomenon has since been proven to affect majority of significant international markets as well as multiple asset classes. Rouwenhorst (1998) found abnormally high returns with strategies similar to Jegadeesh and Titman (1993) in 12 European stock markets, including UK, Germany and France. The effect was present in all size groups, although being stronger in small stocks. The paper also found some correlation between momentum strategy profits of Europe and U.S., leaving open the question of common "momentum factor". In his 1999 paper Rouwenhorst also finds momentum in emerging markets. Interestingly, momentum seems to be absent in listed equities of Japan (e.g. Griffin, Xiuqing and Martin (2003). Moskowitz and Grinblatt (1999) divide stocks into 20 industry portfolios and find the portfolios to experience strong momentum effect. They argue industry momentum to be a strong force behind the momentum effect of individual stocks. Also currencies (e.g. Kho (1996) and commodities (e.g. Erb and Harvey (2006) have been proved to experience the momentum effect.

It has become a standard in the finance literature to call a strategy buying past winners based on prior two to twelve months (*t*-2:12) performance and selling past losers of same interval as *traditional momentum*. This strategy exploits the positive correlation of the past year but excludes the most recent past month because of the short-term return reversal. For example, the performance data obtainable from Kenneth French's data library follows this strategy[1]. 2-to-12-month momentum is used in numerous academic publications e.g. Fama and French (1996) and Daniel and Moskowitz (2016).

The nature of the anomaly has stayed relatively unchanged through the years. Grinblatt and Moskowitz (2004) noticed that "consistent winners" i.e. stocks that have had a steady good performance thorough past months seem to do better than those with just a few extraordinary months to thank from their good past returns. On the other hand, being a "consistent loser" seemed not to have an effect in cross-section of stock returns. Novy-Marx noted in his 2012 article that the momentum effect is primarily caused by the firm performance from 7 to 12 months prior to the formation of the strategy portfolio. This finding undermines the view of momentum as a tendency of well performing stocks to keep performing better than average. Novy-Marx used Fama-Macbeth regressions of securities past returns to show that the explanatory power of the intermediate past performance outweighed that of the more recent, 2 to 6 months returns. This behaviour did not limit to equities, but also applied to commodities and currencies. Moskowitz, Ooi and Pedersen (2012) noted that while previous literature had concentrated on relative performance of stocks i.e. cross-sectional momentum, security's own past return seems also to explain its future profits. They call the phenomena time series momentum and find it different, but related to, cross-sectional momentum and persistent in several major asset classes.

From its initial discovery, reasons for momentum anomaly have been presented plenty. In their original paper Jegadeesh and Titman hypothesize that investors buying winners and selling losers cause the stock market first to overreact (superior returns in intermediate horizon) and that after some time stock prices return to their long-run averages (reversal in longer horizons). They also present an alternative theory that stock market underreacts news on short-term prospects but overreact to those of long-term information value. These two theories,

---

[1] French, K.R., 2018, *Data library*, Tuck School of Business, accessed 15th of December 2017, <http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html>, hereafter referred as "French's data library"

underreaction and delayed overreaction are still behind most of the present behavioural theories for the phenomena (Moskowitz (2010). For example, Daniel, Hirshleifer, and Subrahmanyam (1998) construct a model based on investor overconfidence to justify delayed overreaction and a model by Hong and Stein (1999) uses two types of investors “newswatchers” and “momentum traders” to rationalize underreaction theory. Some models combine the two theories under investor sentiment that explains both under- and overreaction, like that of Barberis, Shleifer and Vishny (1998).

In addition to behavioural theories, rational explanations to momentum have been presented. These theories usually stem from the idea that momentum is simply compensation from risk, and thus can be explained by an asset prising model. This theory is supported by the strong correlation of different momentum strategies that is difficult to explain in behavioural models (Moskowitz and Pedersen (2013). For example, Johnson (2002) suggest stochastic growth rates, that stock prices are depended to, can explain the momentum anomaly at least partly, but also emphasized that finding rational explanations to anomalies like momentum does not mean that markets as a whole would be fully rational. Some more unorthodox views of momentum lack both behavioural and rational explanation. For example, Novy-Marx’s (2012) results of momentum being driven largely by lagged returns from prior seven to 12 months is challenging for current theories.

There are aspects an investor must take into account before undertaking a momentum-driven portfolio. As aforementioned, momentum profits are seasonal, January being traditionally a difficult month for the strategy. A momentum strategy demands frequent portfolio-rebalancing, resulting in transaction costs. Jegadeesh and Titman (1993) found their results reliably significant after taking into account a transaction cost of 0.5%. Korajczyk and Sadka (2004) researched the robustness of momentum portfolios after transaction costs and the price impact of trading; the strategies remained profitable. The authors noted that value weighted strategies performed better post-trading-impact, as they are concentrated on large, liquid stocks. Momentum strategies also encounter infrequent drastic drops in performance called momentum crashes. For example, the traditional momentum portfolio upkeeped in Kenneth French’s data library encountered a drop of 34.4% in April of 2009. Daniel and Moskowitz (2016) noted these crashes to occur after market drawdowns and periods when volatility is high and that they are at least partly predictable.

2.2.Seasonality

Stock prices have been known to follow certain seasonal patterns for decades. These patterns can be dependent on a time of a year, month, week or day. As early as in 1942 Sidney Wachtel noticed that small stocks tend to outperform large ones in January. This “January effect” has since been researched by e.g. Thaler (1987). The holiday effect promises high stock returns during days preceding holidays and has been studied by for example by Lakonishok and Smidt (1988). The monthly effect signifies that positive stock returns are concentrated to the last days and first halves of months (e.g. Ariel (1987). There also exists research on the effect of weekdays: On average the stock market performs poorly on Mondays, as found by Cross (1973) and investigated more recently by e.g. Berument & Kiymaz (2001). Time of day plays a part in stock markets, returns being large at opening and near close of the trading day (Harris (1986). In despite of the wide literature concerning the subject, seasonal cross-sectional variation across returns of individual stocks have, until quite recently, been left with little research.

Heston and Sadka’s 2008 paper can be considered as the birth of the cross-sectional seasonality research. They found a cross-sectional autocorrelation pattern in the U.S. stock returns, in which high positive return autocorrelation recurred in every 12th past lag i.e. yearly. This was caused by a strong seasonal phenomenon: stocks that perform well or badly in a certain calendar month will continue to do so up to 20 years. I consider their paper to be the key previous literature of this Thesis and use methodology similar to them to obtain my results and perform necessary robustness and control checks.

Heston and Sadka built stock trading strategies supported by their research using a sample of NYSE and AMEX -listed equities’ return data from 1945 to 2002. They formed decile portfolios based on returns of past annual lags and compared those to ones built based on all lags and nonannual lags using portfolio formation intervals up to 20 years. They found winners-minus-losers portfolios formed based on all months to give negative returns after the first lagged year, as is expected by the long-term reversal effect, but also that annual-lag portfolios continued to earn profits in all formation intervals. The difference between performance of winners and losers of the annual lags was significant, although smaller on longer horizons. They also noted that the positive returns of a portfolio formed based on the most recent past year could in fact be mainly captured with the first annual lag i.e. buying (selling) stocks that performed well (badly) exactly one year ago.

The authors tested both equal and value weighted strategies. They noticed the phenomena to exist in both, although the returns of value weighted portfolios decreased more in magnitude when examining longer formation intervals. Also, the long-term reversal effect was somewhat smaller in value weighted results. To see whether existing risk factors explain the returns of seasonality strategies, they used the tree factor model by Fama and French (1993) and noticed the risk adjusted returns of annual strategies to remain practically unchanged. They also found the phenomena to sustain economic significance after examining it through various economic methodology.

To test the robustness of the phenomena, Heston and Sadka examined several possible reasons behind the seasonality the cross-section of stock returns. The possible effect of liquidity, in the form of liquidity premium over certain months, was investigated by measuring the abnormal volume. There were large spikes in the average volume effect for the first five annual lags and smaller quarterly liquidity spikes also existed. Volatility of the stock returns was also investigated and similar annual pattern was found but neither volume nor volatility was found to explain the seasonal return patters of winners-minus-losers portfolios.

After dividing their sample to three subgroups based on company market capitalization, they found annual-lag portfolios of large companies to perform better in intermediate formation intervals (2-5 years and 6-10 years) and those made of small companies to yield insignificant returns over longest formation intervals. However, as they concluded, the seasonality phenomena did not seem to be limited to any particular size group. The authors then tested the effect of industry to seasonal returns. The stocks were divided into 20 industries in the spirit of Grinblatt and Moskowitz (1999) and inter-industry component was extracted from the returns. Controlling for industry left majority of seasonal return patterns unexplained.

Heston and Sadka also tested the robustness of seasonal strategies with traditional seasonal phenomena like the January effect and turn-of-the-year. Although seasonality portfolios did yield particularly well in January, the returns were positive in most other months also. They concluded the returns to be non-sensitive to calendar holding period. Next the authors considered fiscal-year-related seasonal events like earnings-announcements and dividends as a potential cause for the abnormal returns. Controlling for earnings announcement had a huge impact on the returns of the first full year, as could be predicted by the findings of Jegadeesh and Titman's original 1993 momentum paper, but changes were subtler in longer formation intervals. Controlling for dividend announcements, ex-dividend months nor fiscal-year-ends did not explain the profitability of seasonality strategy. Finally, they toy with the possibility of potential behavioural reason for the seasonality, but conclude that their findings pose challenging criteria for such explanation to be plausible.

In 2010 Heston and Sadka published a second article on the subject of seasonality, addressing the phenomena in international markets. They found seasonal predictability in stock returns of Japan, Canada and 12 European countries including UK, Germany and France. With fresh data they also confirmed that no data snooping was behind their original U.S. findings. As a primary methodology they sorted stocks into decile portfolios based on their lagged returns excess of local country indexes. Resulting equally weighted combined 14 countries portfolio returns were smaller than their U.S. counterparts, but remained significant up to five-year formation periods. Value weighted returns were more volatile and less significant, probably because of the smaller sample size that emphasized the effect of few large companies.

Keloharju, Linnainmaa and Nyberg (2016) proved the cross-sectional pattern to extend into commodities, stock market indexes and to several market anomalies. They show that rather than these return patterns being a factor in itself, individual securities aggregate seasonalities across factor characteristics. This explains the low correlation between seasonal returns and risk factors tested by Heston and Sadka. Seasonalities seem to originate largely from systematic factors as the strategies have high volatility and seasonal patterns can be observed from diversified portfolios. Further, different seasonal strategies correlate weakly to each other and do not link to macroeconomic variables. The article extends the financial literature by showing seasonal patterns to be of great economic significance and to exist near universally. It serves as the second key previous literature motivating my thesis.

The authors confirm that seasonal patterns exist because of the same-calendar-month performance, as when the historical performance of the month is controlled the pattern practically disappears, excluding the first annual lag. They created well diversified portfolios based on same-calendar-month returns and other-than-same-calendar-month returns and found the results to endorse this view. Factor portfolios were also formed out of stocks exposed to firm characteristics that have been found to correlate on stock returns, such as size, book-to-value and dividend-to-price. Many of factor portfolios were exposed to seasonalities, but they were missing for example from the traditional momentum portfolio.

Keloharju et al. note that seasonal winners-minus-losers strategies are exposed to high systematic risk as they find seasonal strategies considerably riskier than randomly generated ones. This further implies the connection of seasonalities to systematic factors. The authors noticed that seasonal strategies investing to factor portfolios (i.e. size, book-to-market etc.) explain a sizable amount of returns of a “general” seasonal strategy. Keloharju et. al then test returns of anomaly portfolios and notice many of them to follow seasonal pattern i.e. their earnings were dependable on calendar month. The effect remained, although weakened, after January was excluded from the analysis. The authors exploit these dependencies to create an anomaly-portfolio-trading metastrategy that is based on anomalies’ past same-calendar-month-performance with an average monthly return of staggering 1.9%. Even more interestingly, a strategy trading anomalies based on their other-calendar-month performance yields negative returns. This suggests that other than the same-calendar-month performance of an anomaly is irrelevant to its returns in the cross-section of anomalies at a given month. They note that because of this, additional return anomalies can be identified by studying variables accosiated with return seasonalities.

Next the authors test the exposure of seasonality to macroeconomic risks and investor sentiment but found evidence of neither. They proceed to test the robustness of the phenomena and find it persistent in the entire cross section of U.S stock returns and during different subperiods. Seasonalities were also found in commodities and in MSCI country indexes in three continents. Keloharju et al. also note that correlations between different seasonal strategies are low, suggesting that diversification benefits could easily be achieved to multi-strategy investor.

2.3.Seasonal firms-specific events

Several firm-specific events have been proven to effect to the stock price of a company. For example, Loughran and Vijh (1997) found that firms that have completed an acquisition via cash settlement tend to outperform their peers while those that have acquired via stocks underperform. Both initial public offerings and seasonal public offerings have been found to have an effect to stock performance (e.g. Brav, Geczy and Gompers (2000) and Loughran and Ritter (1995). Many of these events are imbedded to the financial year of publicly listed company and most of them are associated with positive abnormal returns (Hartzmark and Solomon (2017). Earnings announcements and dividends have long been thought to be the two most important ways of releasing significant information about the state of the company's state of affairs to the public (e.g. Aharony and Swary (1980). Beaver (1968) discovered that stocks have abnormally large returns around earnings announcements. This earnings announcement premium has since been confirmed and studied further by e.g. Chari, Jagannathan and Ofer (1988) who found the pattern to effect only small companies and also noted that the volatility of the returns increased around earnings announcements.

More recently Savor and Wilson (2016) were able to construct a long-short strategy buying earnings announcers and selling all other stocks with significant profits. They hypothesize that investors incorrectly adjust their earnings expectations for non-announcers through the announcements of other companies. This would increase the systematic risk of announcers and lead to a risk premium. Interestingly Chang, Hartzmark, Solomon and Soltes (2017) noticed that companies yield significant abnormal returns during months with an earnings announcement from a positive seasonality quarter. For example, for a retail store benefiting from Christmas shopping the said positive seasonality quarter would be the fourth. The authors hypothesise that investors overweight recent data and underestimate the predictable seasonal patterns in earnings.

Dividends are another seasonal event for a publicly listed company. Michaely, Thaler and Womack (1995) find that dividend initiation announcements have a positive price impact while omissions have a contrary effect. They also state that reactions to dividend omission announcements are much larger in magnitude. However, Boehme and Sorin (2002) found that while post-dividend-announcement returns are abnormally positive when the abnormal returns are measured against equally weighted portfolios, they become insignificant when value weighted benchmarks are used. Much of research on the effect of dividend announcement is concentrated to study the outcome of unexpected changes in dividends. The subject is also somewhat debated, as for example Watts (1973) founds unexpected changes in dividends to be trivial to future stock price while Aharony and Swary (1980) provide evidence on strong capital market reaction to dividend changes. Aside from the announcement reaction, Hartzmark and Solomon (2013) found that companies predicted to issue dividends in a given month have abnormally positive returns in that month. They hypothesize that this premium is caused by dividend-seeking investors buying stock before the ex-dividend date. Bessembinder and Zhang (2014) found that corporate distribution events, such as dividends and splits can be predicted as they are likely to occur on anniversaries of such events in the history of the individual company. They constructed a trading strategy long on stocks with predicted distribution events and achieved abnormally high returns. The authors state separately that the pattern cannot be explained by the annual seasonality found by Heston and Sadka (2008)

Post-earnings-announcement-drift is one of the most notorious exploitable phenomena accosiated with company specific information releases. It was first discovered as early as 1968 when Ball and Brown noted that stock prices do not fully react to earnings announcements, but that positive (negative) news start an upwards (downwards) drift of the abnormal returns of the stock. Foster, Olsen and Shevlin (1984) constructed a trading strategy long (short) on stocks with large positive (negative) earnings surprises and achieved considerable abnormal returns. They also noted that this phenomenon affects small companies most heavily.

Bernard and Thomas (1990) were able to predict both the sign and magnitude of future price reactions of quarterly earnings announcement up to one year ahead by using current and historical earnings announcement data. In addition to the positive correlation between the earnings surprise for a quarter and post-announcement drift for a next quarter, they found adverse correlation between an earnings surprise of a quarter and abnormal returns around the corresponding quarterly earnings announcement one year in the future. They hypothesize that traders’ future expectations of earnings equal that of comparable time last year. The authors also construct long-short portfolios based on stocks’ historical earnings announcement behaviour and achieve high abnormal returns

3. The Study and Hypotheses

This section will first briefly discusses my personal motivation behind this academic study on quarterly seasonality. To help the reader to identify the concept behind the phenomenon, it will also graph results of cross-sectional regressions of past monthly returns to stock prices like my predecessors Heston and Sadka (2008) and Keloharju et al. (2016). I will then go through my three hypotheses that are initially supported by the results of cross-sectional regressions for this Thesis to investigate further. Lastly, I will address potential gains of this work to finance academia.

Like many in the field of finance, I have always been intrigued by market inefficiencies and anomalies. After familiarizing myself with aggregating studies concerning equity market anomalies, like the excellent study by McLean and Pontiff (2016), I found to be most interested in the effect of past returns to stock price. This was because despite of it being full 25 research-filled years from Jegadeesh and Titman's original paper giving birth to the momentum phenomenon, the anomaly has sustained its spectacularly strong profitability. Inspired by previous research by Novy-Marx (2012) and Heston and Sadka (2008) I formed winners-minus-losers portfolios based on returns of single past lagged returns from the most recent past month all the way up to 240th (unreported). The results of these individual-lagged-month portfolios encouraged me to investigate the effect of lagged quarters.

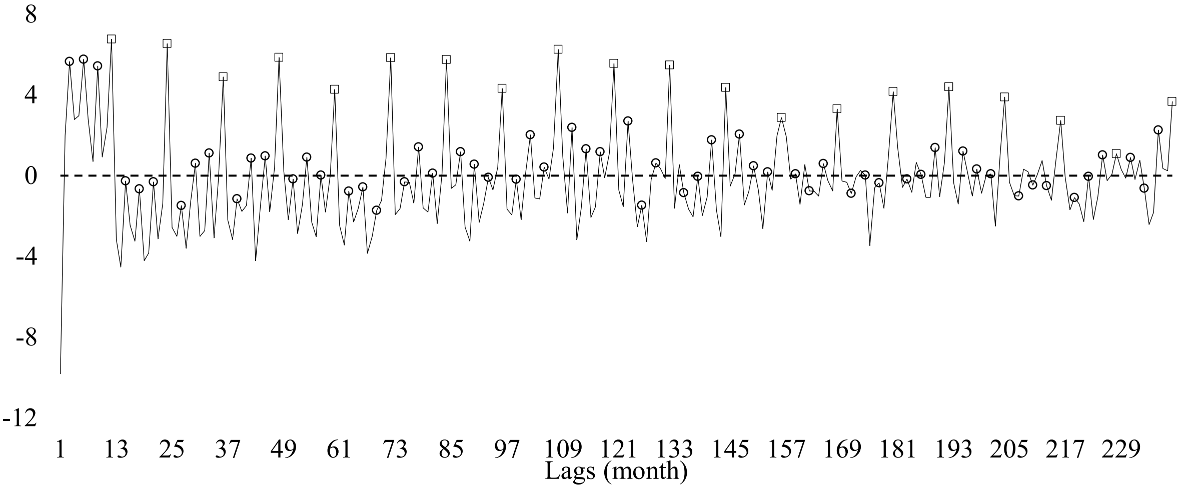
Before further research, I will follow my predecessors Heston and Sadka (2008) and more recently Keloharju et. al. (2016) and calculate cross-sectional effect of past monthly returns to stock prices with Fama and MacBeth (1973) regressions

$$r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + e_{i,t} \qquad \| \; k \epsilon [1,240]$$

where $r_{i,t}$ is the returns of an individual stock *i* at time *t*. Two abovementioned papers plotted the regression coefficients of the results, but I decided to concentrate on the t-values, which can be seen in Figure 1. Also different from my predecessors, I used the data from the entire period of existence of the CRPS database from 1926 to 2016 ergo, as the maximum number of lags taken into account is 240 months, the first returns to be used as dependent variables of the first phase regression are from the January of 1946.

Figure 1 - Effect of past months' returns to stock price

The figure plots t-statistics of Fama and MacBeth (1973) regressions of returns of month *t* against the returns of month *t-k*, $r_{i,t} = \alpha_{k,t} + \gamma_{k,t} r_{i,t-k} + e_{i,t}$, where $k \epsilon$ [1,240]. The squares signify t-statistics of annual lags (*k=12,24,36…*) and circles nonannual quarterend lags (*k=3,6,9,…*). The regressions use monthly data from January 1926 to December 2016 of U.S. stocks reported in CRSP database.



As seen in the Figure 1 past annual lags (*k=12,24,36,…*), marked by squares, clearly stand out from the data as noted first by Heston and Sadka (2008). It is important to clarify that rather than stocks repeating systematic return shocks, this figure is caused by historical performance variation from month to month. For example, a stock that performs well in given December can be expected to continue to do so for a period extending as far as 20 years.

The primary interest of this Thesis lies in the effect of quarterend lags (i.e. *k=3,6,9,…*), marked in the figure as circles (excluding annual quarterend lags abovementioned). The cross-sectional autocorrelation indeed seems to spike also in other quarterend lags than those in annual lags, although the effect is considerably more moderate. Therefore, my first hypothesis is

Hypothesis 1

There exists a significant quarterly-seasonality phenomenon in the stock market. In general, it is more profitable to invest based on stock's quarterend-lag performance than based on its past returns in general.

When conducting a research towards this hypothesis, I have to ensure that the possible performance difference between investment strategies based on quarterend and non-quarterend lagged returns is not built on merely to the strong correlation between the stock returns and *annual* lags already well research by my predecessors. One possibly strategy would be to create portfolios based on nonannual quarterend lags. Confirming the hypothesis would not automatically signify that quarterend strategies would have historically been sensible investments and profitable after, for example, modest trading fees. Although such profit-earning perspective is not the prime objective of this academic work, it is certainly a subject I will also address.

When examining the Figure 1 further, one notices that quarterend lags seem to have particularly strong effect during the already-heavily-correlated first lagged year. This is noteworthy because much of the literature tackling the effect of past returns to stock price concentrates on the effect of these first 12 monthly lags. Traditional momentum strategy buys (sells) stocks that have performed well (badly) during past 2 to 12 months, leaving the most recent month out because of short-term reversal. As quarterend lags constitute four out of eleven months of the momentum phenomena, their contribution to its profits is (and should be) high. However, I am going to go little further and formulate my second hypothesis as

Hypothesis 2

Investment strategy based on quarterend lags (3,6,9 and 12) of the traditional momentum is preferable to a strategy based on all months (2:12).

Preference in investment-sense here denotes better relation of risks and returns measured by the Sharpe ratio (Sharpe 1966) which is, in empirical standpoint, well measured by the t-value of the portfolio returns (Sharpe (1994).

The average correlation of past returns drops after the first full year, as can be expected by the long-term reversal phenomenon. However, the difference between quarterly lags and non-quarterly lags stays surprisingly strong even in more distant intervals. If we leave out the most recent past year, 67% of the quarterend lags have a correlation over zero to a stock return of a given month while only 22% of the non-quarterend lags hold that effect. Nonannual-quarterend lags have positive correlation in 56% of the cases thus the effect of the quarters does not seem to be entirely fuelled by the annual seasonality phenomena. When looking at the lagged years

2-5, the hearth of long-term reversal found by De Bondt and Thaler (1985), quarterly lags seem to persist quite well compared to other lags. Therefore, my third and final hypothesis is

<u>*Hypothesis 3*</u>

Quarterend lags do not contribute to the long-term returns reversal phenomenon found by De Bondt and Thaler (1985).

The quarterly pattern visible in Figure 1 gives little clue of its underlying reasons, of which I will hope to at least partly uncover with my research on the subject. In addition to forming portfolios based on past returns, I have decided to use particular tests to ensure the robustness of my results and to hopefully also shed some light to the origin of the aforementioned pattern. Based on previous research on the matter and the nature of the fiscal year, my prime suspects are company-specific events, many of which encore in quarterly frequencies. Also, I will test the calendar distribution of the returns of my portfolios to see whether the returns are seasonally skewed towards a particular calendar period of the year.

Were these three hypotheses to be proved correct by my research, they would bring new information about the effect of past returns to stock price. Finding a quarterly pattern could help us to better understand the cross-sectional seasonality and its underlying forces. This Thesis could also contribute to the research of long-term reversal literature: Were the quarterend lags found to be exempt of the effect, new potential explanations behind the reversal could arose. Practical, asset management related implications are not entirely out of question, if the quarterend strategies are found to be both feasible and practical investments historically. The most interesting aspect of my work, however, is related to the past intermediate horizon momentum. It is one of, if not the most prominent anomaly against CAPM and bringing new results of the possible forces behind it would be an accomplishment indeed.

4. Data and Methodology

In this section I will first forgo the sources of data necessary for the analysis conducted in my work. Then I will concentrate on methodology used to obtain the results presented in this Thesis. My data consists primarily of time series of U.S. listed stock prices, stocks returns and amounts of shares outstanding and information about security-specific events including earnings announcements and dividend data. My primary research method is formation of monthly-updated portfolios based on past returns.

4.1.Data

My primary source of data is the Center for Research in Security Prices (CRSP), which holds data of returns and various characteristics of U.S. stocks listed in NYSE, Amex and NASDAQ. Like many of my predecessors (for example Daniel & Moskowitz (2016) and Keloharju et al. (2016), I include exclusively ordinary common shares (CRSP code 10 or 11) to my sample. Monthly stock returns data is used from January 1926 to December 2016, consisting of 1092 months. I use CRSP delisting returns to complete the stock returns data and take into account the effect of failing firms to my research. All together my returns sample, excluding particular occurrences addressed later in this chapter, consists of little over 2 million firm months. I decided to use returns free of dividends in my analysis, as companies issuing dividends on quarterly basis could create severe autocorrelation to my results. The effect of this decision is discussed further in this thesis.

When doing a study which involves heavy portfolio formation, one must decide is whether to include low-priced-stocks ("penny stocks") and stocks with "tiny" market capitalization in my sample. In some studies, for example in Jegadeesh and Titman 2001, stock prices lower than $5 USD and securities belonging to the smallest size decile of the New York Stock Exchange have been excluded as Conrad and Kaul (1993) noticed that low-priced stocks contribute heavily to long-term reversal by exhibiting strong returns reversal in January. In their 2010 paper Heston and Sadka did a liquidity control test while investigating the robustness of their international seasonality portfolio returns. They left out stocks priced smaller than equivalent of $5 USD, belonging to smallest priced quarter of securities and stocks with bellow-median trading volume. The magnitude of returns of the seasonal winners-minus-losers portfolios decreased slightly but the distinctive return pattern did not disappear. I decided to exclude stocks priced less than $5 USD from my sample, as I felt that these often illiquid securities would not be suitable for a portfolio updated monthly. The small-cap stocks were kept in the sample to avoid data-snooping.

I will primarily use value weighted portfolio returns, but include equal weighted returns as a robustness check for my prime results, giving an approximation of the effect of small capitalization stocks. For the value weighted portfolios, the equity value for a stock i at month t is calculated as

$$EV_{i,t} = PRC_{i,t} \times SHROUT_{i,t}$$

where PRC and $SHROUT$ are the stock's monthly closing price and its number of shares outstanding from the CRSP database, respectively. The portfolios held during a month t are weighted based on the market capitalization of their participants at month t-1.

For firm-specific-event-related robustness checks, I used CRSP data of dividend announcements and ex-dividend dates. Data of the announcement dates of quarterly earnings from Compustat was used and combined with my CRSP dataset using CRSP/Compustat Merged linked company permanent identification numbers. CRSP lists ex-dividend dates from the beginning of their dataset in 1926 and dividend announcement dates from 1962. Compustat data of earnings announcements starts from July of 1971, but I found the sample size of the first three months insufficient and decided to start using data from the October. For the sake of simplicity and comparability, all event portfolios use data only from October of 1971 onwards, leaving 543 months until the end of my examination period of December 2016. This is roughly half of the period of my stock prices and returns data. In addition to data on individual events, I created a dataset to study the combined effect of all events by merging the previously described event data series. In this combined set a firm was classified as an event-undergoing company at any given month where it encountered any of the abovementioned events. The number of different events beyond one undergone in a given month did not affect the status of the company but the division between event undergoers and non-undergoers was binary.

I calculated my portfolio returns also from a sample consisting exclusively large companies. I felt that this supplemented the results obtained by my actual robustness checks, especially in the case of equally weighted results. However, I decided to leave the results for Appendix for clearer structure of my work. To create a large-company-sample, I used NYSE size deciles obtained from Kenneth French's data library. Companies smaller than the 5^{th} NYSE size decile i.e. median size are excluded but the portfolios are compounded exactly like their full-sample peers. French's data library was also used to obtain the monthly returns of traditional momentum portfolios based on past continuous months for a robustness-check purposes.

4.2.Methodology

The primary empirical vehicle of my research are returns from portfolios based on the performance of past returns. There are certain aspects to be decided on the portfolio constructing methodology. To calculate winners-minus-losers portfolios, one must first decide how to define the said winners and losers. The exact high and low breakpoints of factor characteristics differ from study to study. For example, Kenneth French constructs the traditional long-short momentum portfolio with 70^{th} and 30^{th} return percentiles in his data library, while Heston and Sadka (2008) and Daniel and Moskowitz (2016) use extreme deciles. McLean and Pontiff (2016), who use the high and low quintiles in their study, remark that momentum is an anomaly where higher characteristics exposure leads to higher returns. I decided to use deciles as a basis of my approach as I hope that performance variation among deciles might bring further light to the phenomenon I am researching.

Another question is whether to use equal-weighted or value-weighted returns. Again, there is no unanimous opinion in the literature on matter. McLean and Pontiff (2016) noted that in their sample of 79 anomaly-related studies all but one used primarily equal-weighted returns. Heston and Sadka (2008) also primarily use equal weighting methodology, but note that the annual seasonality pattern is present in both weighting methods. Kenneth French uses value weighted returns of 6 portfolios for his momentum factor. I decided to use value weighted portfolios as my primary approach but also to calculate comparative results from equal weighted portfolios to brought additional level of analysis to my study. The weighting of the portfolio held at a given month *t* is done according to equity values of month *t-1*.

The formation process of portfolios is rather straight-forward. The stocks are divided into ten decile portfolios based on their performance of the given past months. The portfolios are updated monthly. Returns of a losers portfolio i.e. the portfolio formed from the stocks that have performed worse than 90% of the sample of stocks during the lagged months in which a given strategy is based is subtracted from the winners portfolio consisting of the best performed 10%, to create a zero-investment winners-minus-losers (W-L) portfolio. The stocks are selected to portfolios based on average monthly returns instead of cumulative returns. This approach, used e.g. by Heston and Sadka (2008) is more reasonable as majority of my portfolios are based on discontinuous months (i.e. months *t-3,6,9,12*). To sustain comparability of the results this method is also used with portfolios constructed based on continuous months i.e. the full first year strategy (months *t-1:12*). Because of this, my results of the traditional momentum portfolio differ from ones calculated based on cumulative returns.

To be included in a portfolio at a time *t* a stock must have a valid return at time *t* and also an equity value at time *t-1* for value weighting purposes. To ensure full comparability, stock to be accepted into equal weighted portfolio must still have valid equity value for month *t-1*, even if this value is not used in the weighting process whatsoever. Unlike some studies, for example Daniel and Moskowitz (2016), I demand that the security must have valid return data for all the past months used as a basis on construction of a portfolio in question. I know that this requirement reduces my sample, especially with event portfolios discussed below, but I feel this to be necessary because of the non-continuous nature of my formation strategies. All stocks fulfilling these criteria are included into one of the decile portfolios to evade data snooping biases as well as possible.

To test the robustness of my results, the portfolios are tested against the effects of earnings announcements, dividend announcements and ex-dividend dates. These tests are familiar from my predecessors, Heston and Sadka (2008). For each month, two versions of winner and losers portfolios are formed: one built on exclusively stocks with said event occurring during the portfolio holding period and another where such stocks are excluded. This will give an approximation of the effect of these events to my results. In event portfolios, the used stock return data is also restricted to companies that report data of the event in question. For example, out of 20360 companies that reported returns from October 1971 onwards, 18560 (92%) had earnings announcement data available.

In addition to portfolio construction, Fama and MacBeth regressions (1973) were used to calculate cross-sectional effect of past monthly returns to stock price. I ran cross-sectional univariate regressions on the returns of month *t* against months *t-k* where $k\epsilon[1,240]$ for all the months *t*, and then took an average regression estimates and standard errors of each *k* to examine the correlation of past months' returns to stock price. As my returns data starts from January 1926 and I have chosen to examine correlations from lagged 20 years, the regressions are performed from January 1946 onwards, covering 852 months. This is also the calculation period of my portfolio returns excluding the event portfolios.

5. Results

This section presents the results of my Thesis. I will first go through my primary results, the returns of decile portfolios of quarterend strategies compared to those based on other lags. Then I will ensure the originality of the results obtained by leaving out previously investigated annual lags from the portfolios and by testing alternative portfolio weighting methodology. Further robustness checks will also be done by investigating the possible effect of firm-specific seasonal events have to my results. I will then compare the quarterend strategy to traditional momentum portfolio. Finally, the returns of quarterend strategies during individual calendar months is presented.

5.1. Quarterend portfolios

My prime results are decile portfolios based on past quarterend returns. I will compare their performance against portfolios made of non-quarterly lags of selected formation intervals; portfolios formed based on all lags are also shown as benchmark. This style of presentation of the results is familiar from Heston and Sadka (2008). For example, in a given month *t* the *Quarterend* strategy portfolios of the formation interval *Year 1* is built based on the performance of stocks in months *t-3*, *t-6*, *t-9* and *t-12*. Average returns of decile portfolios of all strategies are presented, *W* (winners) signifying portfolios consisting of stocks that have had an average performance higher than 90% of their peers during the given lags, while *L* (losers) have performed worse than 90% of their peers. *W-L* portfolio is calculated in each month simply by subtracting the returns of losers from the winners, creating a market neutral zero-investment portfolio.

Table 1 - Portfolios based on past returns

In a given month *t*, U.S. stocks reported in CRSP database are grouped into ten portfolios based on their past performance, top decile belonging to winner (W) and low decile to loser (L) portfolios. For example, the Quarterend strategy of Year 1 is based on returns of months *t-3*, *t-6*, *t-9* and *t-12* while the All strategy of the same interval is based on months from *t-1* to *t-12*. Winners-minus-losers portfolio (W-L) is created every month by subtracting the returns of losers from winners. Portfolios are updated monthly and average value weighted returns (in percent) and t-statics (in brackets) of all strategies are calculated from January 1946 to December 2016 (852 months).

Strategy		**W**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**L**	**W-L**
	All	1.24%	0.96%	0.89%	0.72%	0.62%	0.61%	0.53%	0.58%	0.48%	0.46%	0.78%
		[5.7]	[5.6]	[5.6]	[4.9]	[4.4]	[4.2]	[3.7]	[3.7]	[2.7]	[2.0]	[3.6]
Year 1	Quarterend	1.39%	1.12%	0.96%	0.70%	0.76%	0.66%	0.51%	0.42%	0.34%	0.14%	1.25%
		[6.6]	[6.5]	[6.3]	[4.8]	[5.3]	[4.8]	[3.5]	[2.8]	[2.0]	[0.7]	[7.3]
	Non-quarterend	1.02%	0.79%	0.67%	0.61%	0.63%	0.69%	0.64%	0.72%	0.70%	0.77%	0.25%
		[4.8]	[4.6]	[4.3]	[4.2]	[4.4]	[4.9]	[4.3]	[4.5]	[3.9]	[3.5]	[1.2]
	All	0.76%	0.73%	0.72%	0.70%	0.75%	0.71%	0.70%	0.85%	0.80%	0.95%	-0.18%
		[3.5]	[4.1]	[4.5]	[4.7]	[5.2]	[5.0]	[5.0]	[5.7]	[5.4]	[5.1]	[-1.1]
Year 2	Quarterend	1.02%	0.83%	0.82%	0.76%	0.68%	0.68%	0.60%	0.56%	0.64%	0.64%	0.38%
		[5.0]	[4.9]	[5.1]	[5.2]	[4.8]	[4.8]	[4.2]	[3.9]	[4.2]	[3.5]	[2.8]
	Non-quarterend	0.60%	0.62%	0.68%	0.65%	0.69%	0.71%	0.77%	0.80%	0.96%	1.18%	-0.58%
		[2.8]	[3.5]	[4.3]	[4.4]	[4.8]	[4.9]	[5.4]	[5.4]	[6.1]	[6.7]	[-3.6]
	All	0.76%	0.69%	0.74%	0.76%	0.68%	0.66%	0.63%	0.76%	0.83%	0.98%	-0.22%
		[3.6]	[4.0]	[4.7]	[5.1]	[4.7]	[4.7]	[4.4]	[5.3]	[5.5]	[5.6]	[-1.5]
Year 3	Quarterend	1.01%	0.90%	0.79%	0.78%	0.74%	0.62%	0.60%	0.51%	0.57%	0.65%	0.36%
		[5.0]	[5.2]	[5.1]	[5.2]	[5.2]	[4.4]	[4.3]	[3.5]	[3.7]	[3.7]	[3.0]
	Non-quarterend	0.66%	0.64%	0.58%	0.63%	0.70%	0.69%	0.78%	0.81%	0.97%	1.11%	-0.45%
		[3.1]	[3.7]	[3.8]	[4.3]	[4.9]	[4.9]	[5.5]	[5.6]	[6.2]	[6.3]	[-3.3]

Strategy		W	2	3	4	5	6	7	8	9	L	W-L
	All	0.85%	0.85%	0.69%	0.66%	0.68%	0.65%	0.73%	0.68%	0.67%	0.88%	-0.02%
		[4.2]	[4.9]	[4.4]	[4.5]	[4.8]	[4.5]	[5.0]	[4.6]	[4.5]	[5.2]	[-0.2]
Year 4	Quarterend	1.02%	0.85%	0.91%	0.69%	0.64%	0.65%	0.62%	0.60%	0.53%	0.58%	0.44%
		[5.2]	[5.1]	[5.8]	[4.7]	[4.5]	[4.5]	[4.5]	[4.2]	[3.5]	[3.3]	[3.6]
	Non-quarterend	0.72%	0.73%	0.63%	0.65%	0.64%	0.72%	0.72%	0.79%	0.85%	0.98%	-0.26%
		[3.6]	[4.3]	[4.1]	[4.3]	[4.5]	[5.0]	[5.0]	[5.4]	[5.7]	[5.7]	[-2.1]
	All	0.85%	0.72%	0.70%	0.70%	0.66%	0.66%	0.71%	0.70%	0.70%	0.83%	0.03%
		[4.2]	[4.3]	[4.5]	[4.7]	[4.5]	[4.7]	[5.0]	[4.9]	[4.8]	[4.8]	[0.2]
Year 5	Quarterend	0.95%	0.86%	0.88%	0.84%	0.74%	0.65%	0.53%	0.54%	0.55%	0.63%	0.31%
		[4.9]	[5.2]	[5.7]	[5.6]	[5.2]	[4.6]	[3.8]	[3.7]	[3.6]	[3.6]	[2.6]
	Non-quarterend	0.70%	0.58%	0.69%	0.59%	0.67%	0.67%	0.75%	0.87%	0.84%	0.97%	-0.28%
		[3.5]	[3.4]	[4.5]	[4.0]	[4.7]	[4.7]	[5.2]	[6.0]	[5.7]	[5.7]	[-2.3]
	All	0.78%	0.63%	0.71%	0.64%	0.61%	0.73%	0.61%	0.78%	0.70%	0.96%	-0.18%
		[3.9]	[3.8]	[4.5]	[4.2]	[4.1]	[5.1]	[4.4]	[5.7]	[5.1]	[6.2]	[-1.3]
Years 6-10	Quarterend	1.04%	0.94%	0.75%	0.74%	0.75%	0.69%	0.64%	0.54%	0.36%	0.31%	0.73%
		[5.5]	[5.7]	[4.9]	[5.0]	[5.1]	[4.9]	[4.6]	[3.7]	[2.5]	[2.0]	[5.8]
	Non-quarterend	0.62%	0.48%	0.51%	0.51%	0.61%	0.71%	0.82%	0.86%	0.79%	1.12%	-0.51%
		[3.2]	[2.9]	[3.3]	[3.5]	[4.3]	[4.8]	[5.8]	[6.2]	[5.6]	[7.3]	[-3.8]
	All	0.71%	0.78%	0.72%	0.67%	0.62%	0.61%	0.69%	0.75%	0.63%	0.75%	-0.04%
		[4.1]	[5.0]	[4.9]	[4.6]	[4.3]	[4.0]	[4.7]	[5.2]	[4.3]	[4.6]	[-0.3]
Years 11-15	Quarterend	0.83%	0.81%	0.73%	0.83%	0.68%	0.55%	0.68%	0.57%	0.49%	0.39%	0.45%
		[5.0]	[5.4]	[5.0]	[5.6]	[4.7]	[4.0]	[4.7]	[3.8]	[3.3]	[2.5]	[4.2]
	Non-quarterend	0.55%	0.59%	0.72%	0.65%	0.67%	0.72%	0.68%	0.66%	0.74%	0.88%	-0.33%
		[3.3]	[3.9]	[4.7]	[4.4]	[4.7]	[5.0]	[4.7]	[4.6]	[4.9]	[5.7]	[-3.1]
	All	0.71%	0.62%	0.70%	0.65%	0.63%	0.65%	0.70%	0.67%	0.51%	0.81%	-0.10%
		[4.2]	[4.0]	[4.7]	[4.4]	[4.3]	[4.6]	[4.9]	[4.8]	[3.6]	[5.1]	[-0.8]
Years 16-20	Quarterend	0.75%	0.79%	0.75%	0.77%	0.70%	0.65%	0.63%	0.50%	0.46%	0.46%	0.29%
		[4.6]	[5.1]	[5.1]	[5.2]	[4.9]	[4.6]	[4.3]	[3.5]	[3.2]	[2.8]	[2.6]
	Non-quarterend	0.60%	0.64%	0.66%	0.61%	0.53%	0.71%	0.55%	0.74%	0.80%	0.84%	-0.24%
		[3.5]	[4.0]	[4.5]	[4.2]	[3.5]	[5.0]	[3.9]	[5.2]	[5.5]	[5.3]	[-2.1]

Encouraged by the Figure 1, I decided to concentrate on short and intermediate portfolio formation intervals. Out of eight intervals I have selected for the study, five are based on the performance of a lagged individual year, starting from the most recent. Longer formation periods are divided into three strategies, intervals of years 6-10, 11-15 and 16-20. My principal point on interest is the lagged first year, as much of the academic research concerning the effect of past returns is concentrated on these most recent 12 lagged months. I decided to address the first five past years individually as many research on the effect of long-term reversal, for example that of De Bondt and Thaler's (1985), deals with lags up to five years. The long scope of 20 years in total was selected in the spirit of previous seasonality literature (Heston and Sadka (2008) and Keloharju et al. (2016). The intervals of 10-15 and 16-20 also serve as a good reference as the quarterly pattern shown in Figure 1 seems to decay during this time.

Data from the year 1926 onwards is used (the start of CRSP database). The longest formation period extends to lagged 20 year returns and to sustain the comparability of the results, all portfolios are formed and average returns calculated from the year 1946 onwards. Average returns and t-statistics of decile portfolios are presented in Table 1. The results look promising. Quarterend strategies outperform other strategies at all formation intervals. Despite of the long-term reversal effect, the returns of quarterend strategies remain significantly positive thorough the lagged 20 years. When intercepting this finding it is important to keep in mind that I have removed stocks priced less than $5 USD which, according to Conrad and Kaul (1993), will reduce the effect of long-term reversal. W-L portfolios formed based on all months earn positive returns on first year and negative returns in longer lags (with the exception of *Year 5*), as one would expect based on previous returns of the momentum phenomena and long-term reversal. The magnitude of my results seems plausible when compared to those of previous literature.

As expected by the previous literature on the effect of past returns, all W-L strategies based on the most recent past year are positive. However, the magnitude of spread between quarterend and non-quarterend returns is striking, 1.00 percentage point per month i.e. the spread is larger than the profits of a strategy based on the full past year. The differences in t-values, signifying portfolio Sharpe -ratios (Sharpe (1994), are even more prominent: quarterend strategy's t-value of 7.3 is large compared to those of all lags (3.6) and non-quarterend lags (1.2). In fact, the t-value of non-quarterend portfolio is not significant in commonly used parameters, although it must be kept in mind that the performance of both full one-year portfolio and non-quarterend portfolio are probably heavily affected by the short-term reversal, the effect of the most recent monthly lag. Quarterend months seem to have a huge impact on the returns of strategies trading stocks based on their past-year-performance and furthermore, investing into stocks that have performed well in past 4 quarters seem to be more lucrative and less risky than on investing based on past 12 months.

The profitability of all W-L strategies decays in longer lags, as can be expected by Figure 1 and the long-term reversal phenomena. The quarterend strategy, however, remains significantly positive on 5% level on all formation intervals. There is surprisingly little deviation in the profits of the quarterend strategies in individual years 2-5. The returns of W-L portfolios based on all lags are not significantly negative in any formation period. This seems to be because of the effect of quarterend lags, however, as non-quarterend portfolios indeed are all significantly negative after the first year. It is important to take into account, that the survivorship bias increases in longer portfolio intervals, like noted by Heston and Sadka (2008). Only selected companies will ever have a return history of 20 years. This effect is diluted by my large sample size consisting of all common stocks in the CRSP data with exceptions mentioned in the Data section of this thesis. The effect is presumably more significant in the early years of the period of my portfolio returns calculation, because of the smaller number of companies.

When looking at the performance of individual deciles beyond W and L portfolios, one notices that returns of quarterend portfolios follow a distinctive decreasing pattern when moving from winner deciles to loser ones with only some exceptions. The differences in t-values are somewhat broader, but clearly follow similar pattern. The patterns are near perfectly reversed when non-quarterend strategies are observed, last deciles performing better than winners. The *Year 1* of *Non-quarterend* strategy makes an exception by having little apparent pattern besides the superior performance of the winner portfolio. This may be because of the strength of the intermediate-term momentum phenomena.

These results crave for a series of further research and robustness checks. Annual lags are previously proved to hold a significant effect to stock price and they are thus affecting the returns of my quarterend portfolios. That quarterend strategies outperforming others could in fact be nothing but a diluted echo of the effect of annual lags. I will continue this Thesis by forming quarterend portfolios that exclude the said annual lags to research whether quarterly lags hold an effect of their own. I am also interested in how does my selected portfolio allocation method, weighting based on market capitalization, affect to the results. I will calculate equal weighted returns out of my quarterend portfolios to investigate this matter and to supplement my value weighted results.

Some firm-specific, seasonal events will almost certainly hold an effect to my results, most important of these being quarterly earnings-announcements, dividend-announcements and ex-dividend dates. In the spirit of Heston and Sadka (2008) I will compare portfolios built with event and non-event stocks to isolate the effect of these occurrences. Finally, the results seen here encourage for further research on the traditional momentum phenomena. As *Year 1* strategies *All* and *Non-quarterend* computed here take into account the most recent annual lag, they are exposed to short-term reversal effect thus further investigation on the matter require a portfolio based on lags 2-12 to be computed. This is done later in my thesis.

5.2.Effect of annual lags

Although my results are encouraging, one will easily wonder how much of the quarterly seasonality can be explained by the annual lags already well research by Heston and Sadka (2008) and Keloharju et al. (2016). To distinguish the portion of the returns of lagged quarters I created nonannual quarterend strategies for all formation intervals. For example, the *Year 1* nonannual quarterend strategy winners-minus-losers portfolio buys (sells) stocks that have performed well (badly) in lagged months 3, 6 and 9. Table 2 shows the resulting average returns and t-statistics of the decile portfolios in all eight formation intervals. The data and methodology are identical to those of earlier results.

As could be expected from the Figure 1, the average returns of all *W-L* portfolios decrease when annual lags are omitted. However, returns of my principal point of interest, the portfolio based on nonannual quarterends of the first year, will remain significantly positive. The spread of monthly profits versus the full quarterend strategy is 23 basis points. Remarkably, the nonannual quarterend strategies still outperform strategies based on *all* months, including annual lags, in every single formation period. Decile portfolio comparison of nonannual quarterend strategies reveals patterns very similar to full quarterend strategies. It comes to no surprise that none of the other individual year strategies yield significantly positive winners-minus-losers portfolio. Then, one could be surprised that none of the W-L strategies of the years 2-5 have negative average returns either! Indeed, it seems that lagged quarters do not contribute to long-term reversal effect reported by De Bondt and Thaler (1985). This finding strongly supports my *Hypothesis 3* and I consider it to be one of the most prominent findings of my Thesis and an excellent topic for further research.

Table 2 – Nonannual quarterend portfolios

In a given month *t*, U.S. stocks reported in CRSP database are grouped into ten portfolios based on their past nonannual quarterend performance, top decile belonging to winner (W) and low decile to loser (L) portfolios. For example, the Year 2 strategy is based on returns of months *t-15*, *t-18* and *t-21*. Winners-minus-losers portfolio (W-L) is created every month by subtracting the returns of losers from winners. Portfolios are updated monthly and average value weighted returns (in percent) and t-statics (in brackets) of all strategies are calculated from January 1946 to December 2016 (852 months).

Strategy	**W**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**L**	**W-L**
Year 1	1.32%	1.05%	0.85%	0.74%	0.72%	0.63%	0.64%	0.49%	0.39%	0.30%	1.02%
	[6.3]	[6.1]	[5.4]	[5.2]	[5.1]	[4.4]	[4.5]	[3.2]	[2.2]	[1.5]	[5.9]
Year 2	0.80%	0.81%	0.72%	0.80%	0.71%	0.69%	0.65%	0.69%	0.63%	0.79%	0.01%
	[3.9]	[4.7]	[4.7]	[5.4]	[5.0]	[4.9]	[4.6]	[4.7]	[4.0]	[4.3]	[0.1]
Year 3	0.92%	0.79%	0.83%	0.74%	0.73%	0.68%	0.59%	0.60%	0.51%	0.83%	0.09%
	[4.6]	[4.7]	[5.2]	[5.0]	[5.1]	[4.8]	[4.1]	[4.0]	[3.3]	[4.7]	[0.7]
Year 4	0.88%	0.86%	0.80%	0.70%	0.63%	0.73%	0.67%	0.62%	0.62%	0.70%	0.18%
	[4.4]	[5.2]	[5.2]	[4.8]	[4.4]	[5.2]	[4.7]	[4.2]	[3.9]	[3.9]	[1.5]
Year 5	0.85%	0.82%	0.78%	0.79%	0.71%	0.74%	0.61%	0.51%	0.60%	0.70%	0.15%
	[4.4]	[4.9]	[5.2]	[5.4]	[4.9]	[5.1]	[4.3]	[3.5]	[3.8]	[4.0]	[1.2]
Years 6-10	0.86%	0.80%	0.67%	0.72%	0.73%	0.74%	0.61%	0.72%	0.49%	0.53%	0.33%
	[4.7]	[4.8]	[4.3]	[4.9]	[5.0]	[5.2]	[4.3]	[5.0]	[3.4]	[3.4]	[2.8]
Years 11-15	0.84%	0.60%	0.83%	0.70%	0.63%	0.71%	0.55%	0.61%	0.53%	0.62%	0.22%
	[4.9]	[4.0]	[5.7]	[4.8]	[4.3]	[4.8]	[3.8]	[4.1]	[3.5]	[4.0]	[2.0]
Years 16-20	0.64%	0.75%	0.75%	0.70%	0.67%	0.58%	0.61%	0.60%	0.53%	0.66%	-0.02%
	[3.8]	[4.8]	[5.0]	[4.8]	[4.6]	[4.1]	[4.3]	[4.2]	[3.6]	[4.1]	[-0.1]

The *W-L* portfolios of strategies 6-10 and 11-15 yield significantly positive returns even when the annual lags have been removed from the analysis. This finding is surprising and cannot be explained by the survivorship bias as the 16-20 strategy yields returns close to zero. I find no apparent explanation for this other than the result seems plausible when examining the cross-sectional correlations in Figure 1. Altogether, it seems that the quarterly seasonality is a phenomenon at least partly independent from annual seasonality in the stock market. On the other hand, I find it reasonable to hypothesize that there exists an autocorrelation between the two seasonality patterns, i.e. also a part of annual seasonality can be explained by quarterend return pattern.

5.3.Equally weighted returns

I am interested about the effect of my chosen portfolio weighting method to my results. Heston and Sadka (2008) noticed that the long-term reversal had some more affect to equal weighted strategies but the results of annual seasonality portfolios stayed within the same magnitude in both equal and value weighted. The Table 3 lists decile portfolio average returns and t-statistics of equally weighted quarterend portfolios. All other factors concerning the data and methodology are identical to Table 1.

Table 3 - Equally weighted portfolios based on quarterend lags

In a given month *t*, U.S. stocks reported in CRSP database are grouped into ten portfolios based on their past performance, top decile belonging to winner (W) and low decile to loser (L) portfolios. For example, the Year 1 strategy is based on returns of months *t-3*, *t-6*, *t-9* and *t-12*. Winners-minus-losers portfolio (W-L) is created every month by subtracting the returns of losers from winners. Portfolios are updated monthly; stocks are given equal weights and average returns (in percent) and t-statics (in brackets) of all strategies are calculated from January 1946 to December 2016 (852 months).

Strategy	W	2	3	4	5	6	7	8	9	L	W-L
Year 1	1.58%	1.34%	1.22%	1.09%	0.99%	0.93%	0.89%	0.80%	0.74%	0.70%	0.88%
	[7.4]	[7.5]	[7.5]	[7.1]	[6.5]	[6.2]	[5.8]	[5.0]	[4.2]	[3.3]	[7.0]
Year 2	1.29%	1.23%	1.14%	1.07%	1.07%	1.00%	0.99%	0.99%	1.07%	1.34%	-0.04%
	[6.2]	[6.9]	[6.8]	[6.8]	[6.9]	[6.6]	[6.4]	[6.4]	[6.3]	[6.7]	[-0.5]
Year 3	1.44%	1.27%	1.16%	1.10%	1.06%	1.04%	1.03%	1.02%	1.07%	1.37%	0.07%
	[6.9]	[7.0]	[7.1]	[7.0]	[6.9]	[6.9]	[6.8]	[6.5]	[6.4]	[6.9]	[0.8]
Year 4	1.48%	1.28%	1.18%	1.12%	1.03%	1.04%	1.03%	1.03%	1.07%	1.33%	0.15%
	[7.2]	[7.3]	[7.2]	[7.1]	[6.7]	[6.8]	[6.8]	[6.6]	[6.4]	[6.9]	[1.9]
Year 5	1.41%	1.21%	1.18%	1.13%	1.07%	1.05%	0.99%	1.05%	1.05%	1.37%	0.04%
	[7.1]	[7.0]	[7.2]	[7.1]	[7.0]	[7.0]	[6.5]	[6.6]	[6.3]	[7.2]	[0.5]
Years 6-10	1.43%	1.17%	1.06%	1.00%	1.02%	0.95%	0.92%	0.93%	0.86%	0.81%	0.62%
	[7.6]	[7.0]	[6.8]	[6.5]	[6.8]	[6.5]	[6.2]	[6.2]	[5.5]	[4.9]	[7.8]
Years 11-15	1.22%	1.09%	1.03%	1.03%	0.97%	0.91%	0.97%	0.89%	0.79%	0.86%	0.36%
	[7.1]	[6.7]	[6.6]	[6.7]	[6.4]	[6.0]	[6.5]	[5.8]	[5.2]	[5.3]	[5.2]
Years 16-20	1.10%	1.02%	0.97%	0.94%	0.93%	0.86%	0.87%	0.82%	0.82%	0.77%	0.33%
	[6.4]	[6.4]	[6.2]	[6.3]	[6.2]	[5.8]	[5.8]	[5.3]	[5.4]	[4.6]	[4.3]

All average returns of equally weighted W-L portfolios are smaller than their value weighted peers, with the exception of formation interval 16-20 years. The differences are large in magnitude, especially in intervals longer than one year. Indeed, out of individual year portfolios after the Year 1, only the Year 4 portfolio has returns statistically significant at even 10% level. The returns of longer interval W-L portfolios are again remarkably significant. When taking into account the strong *annual* seasonality in equal weighted portfolios proved by my predecessors, nonannual quarterend lags unlikely hold little explanatory power. The average returns of the Year 1, the point of highest interest in this Thesis, are smaller in equally weighted portfolios, 88 bps monthly compares to 125 bps in value weighted. However, the equally weighted portfolio also has considerably smaller standard error, leading to the t-value on 7.0 which is comparable to 7.3 of the value weighted strategy. This is not only true for the Year 1 results, but the standard errors of W-L portfolios of equal weighted strategies are all smaller than their value weighted peers. The finding is reasonable, as the returns of value weighted portfolios are more exposed to single large companies.

Analysis of the decile portfolios reveals that the relatively weaker performance of equal weighted W-L portfolios is result of better performance of equal weighted portfolios overall. Every equal weighted winner portfolio performs better than its value weighted peer, but so do the equal weighted loser portfolios and in fact *every single comparable decile portfolio*, leading to ultimately smaller returns of zero-investment portfolios. It is strange that the equally weighted *W-L* portfolios at longer formation intervals of 6-20 years actually have t-values remarkably stronger than their value weighted peers while the individual year portfolios through 2-5 are so much weaker. Finding an exhaustive explanation to this is hard with my methodology, but it could be that the survivorship bias mentioned by Heston and Sadka is stronger in small cap stocks.

By these results it seems that quarterly seasonality affects weaker to small stocks. This finding is interesting and I will further analyse it in the Discussion chapter of this work. In despite of this oddity, the returns of *Year 1 W-L* portfolio are promising. I decided to include also equally weighted returns into the more thorough analysis of the first lagged year later in this chapter to further investigate the effect of the weighting method to my most important results.

5.4. Firm-specific events

I will perform an analysis similar to Heston and Sadka (2008) to control the effects of quarterly earnings announcement, dividend announcements and ex-dividend dates to my results. Compustat data of company earnings announcements and CRSP data of dividend announcement and ex-dividend dates are used from October 1971 and decile portfolio returns are calculated from October 1976 onwards to obtain the average returns of the strategies. In addition to these thee individual event tests, I test the pooled effect of all the three events with a combined dataset. On every month, two versions of all the event portfolios are formed: one with only companies undergoing the said event, e.g. an earnings announcement in the given month (an *event* portfolio) and another where event-undergoing companies are excluded from the portfolio formation (a *nonevent* portfolio). In the combined all-event portfolios, companies undergoing *any* of the three events are classified as an event undergoes. The company samples are limited to firms that report said event in question to ensure comparability.

I think that these robustness checks are even more important for the quarterend portfolios than they are when researching the annual seasonality. Earnings announcements are a quarterly event *by definition* and dividends are usually issued by quarterly intervals by U.S. companies (e.g. Ferris, Noronha and Unlu (2010) report that 87% of U.S. companies in their sample pay dividends on quarterly frequency). Therefore, I decided to include the event and non-event strategy comparison not only for my quarterend strategies but also for all lags and non-quarterend lags-based strategies. Like Heston and Sadka (2008), I do not report the results of each decile portfolio but only the results of W-L portfolios of event and nonevent strategies. This is done for the sake of structure of my work. I chose to include these event robustness checks only from the first five portfolio formation intervals (i.e. the five most recent individual years), omitting the longest three. I expect the possible effects of the events to be visibly enough for necessary assumptions to be made from these results. The average returns and t-statistics of W-L portfolios are presented in Table 4.

Table 4 - Portfolios controlling for firm-specific events

In a given month *t*, U.S. stocks that have returns reported in CRSP database and event-specific information available in CRSP/Compustat are grouped into ten portfolios based on their past performance, top decile belonging to winner and low decile to loser portfolios. For example, the Quarterend strategy of Year 1 is based on returns of months *t-3*, *t-6*, *t-9* and *t-12* while the All strategy of the same interval is based on months from *t-1* to *t-12*. Event (nonevent) portfolios consists of companies that undergo (do not undergo) the said event on month *t*. Only the returns of winners-minus-losers portfolios are presented. They are created every month by subtracting the returns of losers from winners. Portfolios are updated monthly and average value weighted returns (in percent) and t-statics (in brackets) of event and nonevent portfolios are calculated from October 1976 to December 2016 (483 months).

		Earnings announcement		**Dividend announcement**		**Ex dividend day**		**All events**	
Strategy		event	nonevent	event	nonevent	event	nonevent	event	nonevent
	All	0.64%	0.67%	0.54%	0.69%	0.36%	0.73%	0.33%	0.78%
		[1.6]	[2.0]	[1.8]	[2.0]	[1.1]	[2.2]	[1.0]	[2.3]
Year 1	Quarterend	1.05%	1.06%	1.11%	1.16%	1.03%	1.08%	1.04%	1.00%
		[3.2]	[3.9]	[4.4]	[4.1]	[3.8]	[4.0]	[3.8]	[3.4]
	Non-quarterend	-0.26%	0.43%	0.10%	0.31%	-0.06%	0.36%	-0.11%	0.45%
		[-0.7]	[1.5]	[0.4]	[1.0]	[-0.2]	[1.2]	[-0.4]	[1.4]
	All	0.08%	-0.01%	0.07%	-0.19%	0.23%	-0.18%	0.13%	-0.13%
		[0.2]	[-0.0]	[0.3]	[-0.8]	[1.0]	[-0.7]	[0.6]	[-0.5]
Year 2	Quarterend	0.46%	0.08%	0.16%	0.18%	0.58%	-0.01%	0.46%	-0.09%
		[1.6]	[0.4]	[0.7]	[0.8]	[2.5]	[-0.0]	[2.1]	[-0.4]
	Non-quarterend	-0.46%	-0.36%	-0.23%	-0.57%	0.00%	-0.56%	-0.35%	-0.30%
		[-1.5]	[-1.5]	[-1.0]	[-2.3]	[-0.0]	[-2.3]	[-1.5]	[-1.2]
	All	-0.88%	-0.11%	0.09%	-0.30%	0.40%	-0.40%	-0.11%	-0.28%
		[-2.9]	[-0.5]	[0.4]	[-1.4]	[1.8]	[-1.9]	[-0.5]	[-1.2]
Year 3	Quarterend	-0.42%	0.28%	0.34%	0.10%	0.38%	0.04%	0.05%	0.28%
		[-1.5]	[1.5]	[1.5]	[0.6]	[1.7]	[0.2]	[0.2]	[1.3]
	Non-quarterend	-0.93%	-0.17%	-0.08%	-0.41%	0.28%	-0.56%	-0.53%	-0.27%
		[-3.1]	[-0.9]	[-0.4]	[-1.9]	[1.2]	[-2.7]	[-2.5]	[-1.2]
	All	0.12%	0.16%	-0.04%	0.06%	0.43%	-0.13%	0.11%	0.02%
		[0.4]	[0.7]	[-0.1]	[0.3]	[1.9]	[-0.6]	[0.5]	[0.1]
Year 4	Quarterend	0.13%	0.66%	0.35%	0.48%	0.88%	0.28%	0.50%	0.62%
		[0.5]	[3.2]	[1.5]	[2.6]	[4.1]	[1.5]	[2.4]	[2.8]
	Non-quarterend	0.06%	-0.19%	-0.12%	-0.10%	0.24%	-0.29%	0.03%	0.03%
		[0.2]	[-1.0]	[-0.5]	[-0.5]	[1.1]	[-1.4]	[0.1]	[0.1]
	All	0.07%	0.15%	-0.17%	-0.02%	0.15%	-0.08%	0.00%	0.17%
		[0.2]	[0.8]	[-0.7]	[-0.1]	[0.7]	[-0.4]	[-0.0]	[0.8]
Year 5	Quarterend	0.29%	0.21%	0.49%	0.21%	0.59%	0.01%	0.62%	-0.08%
		[1.1]	[1.1]	[2.1]	[1.1]	[2.7]	[0.1]	[2.9]	[-0.4]
	Non-quarterend	0.05%	-0.07%	-0.54%	-0.08%	-0.23%	-0.16%	0.02%	-0.43%
		[0.2]	[-0.4]	[-2.3]	[-0.4]	[-1.1]	[-0.9]	[0.1]	[-2.2]

When intercepting the results, one must keep in mind that as, for example, earnings announcements are carried out four times a year, the sample sizes of event and non-event portfolios of a given strategy are not equal: in average the event portfolio has a sample size one half of that of non-event portfolio. This leads to event strategies being less diversified ergo having larger expected standard errors leading to smaller t-values. This fact may be further driven by my choice of portfolio valuation technique, as value weighting emphasizes the returns of huge companies. However, I deemed necessary that these robustness checks should be carried out by the same methodology as the body of my results to sustain their credibility. In *All events* portfolio the sample sizes of event and nonevent portfolios are closely comparable. The results obtained by these robustness checks should not be compared to my prime results in Table 1 per se, as both the sample time period and number of companies qualified is limited in the first-mentioned.

Quarterend strategies continue to outperform other strategies in all portfolios except for the Year 3 *Ex-dividend day* event and Year 5 *All events* nonevent comparison. This is an encouraging sign and can be interpret as the most important finding of these robustness checks. None of the events investigated, nor a combination of them, seem to invalidate the fact that portfolios based on quarterend lags earn a premium over other strategies, although here it must be kept in mind that these quarterend portfolios include the powerful annual lag already researched by my predecessors. On average, the spreads between *quarterend* and *non-quarterend* strategies of event and nonevent portfolios are smaller than in my prime results. Also, in the case of *All events* strategies, this spread is on average higher in event portfolios than in nonevent portfolios (72 bps v. 45 bps). The t-statistics of the event and nonevent quarterend strategies are smaller than their Table 1 counterparts, as can be expected by the shorter sample time frame.

When analysing event v. nonevent spreads of the Year 1, the returns of event strategies are generally smaller than their non-event counterparts. This is particularly true in the case of non-quarterend portfolios. In quarterend strategies, however, the differences are small, within 5 basis points. All event and nonevent quarterend strategies remain their significance in the most recent portfolio formation interval. Analysing the individual events, the median effect of earnings announcements and dividend announcements is close to zero in all strategies. However, excluding the most recent past year, companies seem to yield better returns in months that undergo ex-dividend dates. In *All events* portfolios, the differences again are small: studied firm events seem to have little effect to the returns of my strategies.

Despite of the fact that quarterend strategies preserved their edge, the results of event portfolios are surprising compared to previous research. For example, Heston and Sadka (2008) noted the earnings announcement event portfolio based of all months of the first lagged year to have significantly higher returns than the non-event portfolio, while on my returns the non-event portfolio yields slightly better profits. Heston and Sadka's results are backed by for example the findings by Jegadeesh and Titman (1993); the profits of momentum portfolios are concentrated around earnings announcements. The most prominent explanation to this finding is my choice of weighting methodology, my different time sample and my decision to leave stocks priced under $5 from my analysis. These issues are discussed further in this thesis.

5.5. Traditional momentum

The results of Tables 1 and 3 motivate me to further investigate the traditional from 2 to 12 months momentum effect. I am interested of how much of the momentum profits can be explained by the profits of quarter end months i.e. 3^{rd}, 6^{th}, 9^{th} and 12^{th} lag. Heston and Sadka (2008) noticed that portfolio constructed based on just the 12^{th} lag had higher t-value that that of full-one-year portfolio. However, they included the first monthly lag in their full-one-year portfolio, that unquestionably weakened its profits because of the strong short-term reversal phenomena. I will exclude the first lagged month from the analysis and include a portfolio based on non-quarterend months of the traditional momentum, i.e. monthly lags of 2,4,5,7,8,10 and 11. The average returns and t-statistics are presented in Table 5. Results from both value weighted and equal weighted portfolios are shown for further evidence. The table also includes quarterend strategy and nonannual quarterend strategy already reported in the former parts of this thesis. This is because I consider this table to have the most significant findings of my work and I prefer easy comparability of the results. Portfolios based on just the first annual lag are also present to distinct its effect.

Table 5 - Portfolios based on intermediate-term past returns

In a given month *t*, U.S. stocks reported in CRSP database are grouped into ten portfolios based on their past performance, top decile belonging to winner (W) and low decile to loser (L) portfolios. The strategies are named based on the lagged returns on which their returns are based, *2:12* being the "traditional momentum" strategy of the past one year excluding the month recent past month. Winners-minus-losers portfolio (W-L) is created every month by subtracting the returns of losers from winners. Portfolios are updated monthly and average returns (in percent) and t-statics (in brackets) of all strategies are calculated from January 1946 to December 2016 (852 months). Results of both value and equal weighted portfolios are presented.

Strategy		**W**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**L**	**W-L**
	2:12	1.35%	1.05%	0.87%	0.78%	0.66%	0.59%	0.53%	0.49%	0.39%	0.26%	1.10%
		[6.1]	[6.1]	[5.5]	[5.2]	[4.5]	[4.2]	[3.7]	[3.1]	[2.2]	[1.2]	[5.1]
	3,6,9,12	1.39%	1.12%	0.96%	0.70%	0.76%	0.66%	0.51%	0.42%	0.34%	0.14%	1.25%
		[6.6]	[6.5]	[6.3]	[4.8]	[5.3]	[4.8]	[3.5]	[2.8]	[2.0]	[0.7]	[7.3]
Value weighted	2,4,5,7,8,10,11	1.13%	0.88%	0.70%	0.66%	0.62%	0.64%	0.62%	0.62%	0.64%	0.59%	0.54%
		[5.2]	[5.1]	[4.6]	[4.5]	[4.3]	[4.5]	[4.2]	[4.0]	[3.7]	[2.8]	[2.9]
	3,6,9	1.32%	1.05%	0.85%	0.74%	0.72%	0.63%	0.64%	0.49%	0.39%	0.30%	1.02%
		[6.3]	[6.1]	[5.4]	[5.2]	[5.1]	[4.4]	[4.5]	[3.2]	[2.2]	[1.5]	[5.9]
	12	1.17%	0.96%	0.89%	0.78%	0.72%	0.65%	0.53%	0.49%	0.49%	0.40%	0.77%
		[5.6]	[5.5]	[5.7]	[5.2]	[5.0]	[4.6]	[3.7]	[3.3]	[3.0]	[2.2]	[5.1]
	2:12	1.55%	1.31%	1.15%	1.03%	0.97%	0.88%	0.78%	0.74%	0.70%	0.76%	0.79%
		[6.9]	[7.3]	[7.1]	[6.7]	[6.5]	[5.9]	[5.1]	[4.6]	[3.9]	[3.4]	[4.6]
	3,6,9,12	1.58%	1.34%	1.22%	1.09%	0.99%	0.93%	0.89%	0.80%	0.74%	0.70%	0.88%
		[7.4]	[7.5]	[7.5]	[7.1]	[6.5]	[6.2]	[5.8]	[5.0]	[4.2]	[3.3]	[7.0]
Equal weighted	2,4,5,7,8,10,11	1.34%	1.11%	1.02%	0.97%	0.92%	0.92%	0.91%	0.94%	0.89%	0.98%	0.36%
		[6.1]	[6.2]	[6.3]	[6.2]	[6.1]	[6.0]	[5.9]	[5.8]	[5.1]	[4.6]	[2.4]
	3,6,9	1.58%	1.26%	1.16%	1.08%	1.02%	0.96%	0.92%	0.83%	0.85%	0.82%	0.76%
		[7.5]	[7.2]	[7.1]	[7.0]	[6.8]	[6.4]	[5.9]	[5.1]	[4.7]	[3.8]	[5.7]
	12	1.66%	1.36%	1.27%	1.16%	1.12%	1.07%	1.01%	1.02%	0.98%	1.12%	0.54%
		[7.5]	[7.4]	[7.5]	[7.3]	[7.2]	[7.0]	[6.5]	[6.3]	[5.6]	[5.4]	[5.1]

The results seem favourable to Hypothesis 2. The portfolio based on the most recent four quarterend lags gives higher average returns and a larger t-value, indicating a higher Sharpe-ratio (Sharpe (1994), than a traditional momentum portfolio in both value weighted and equal weighted results. It seems that profits of the momentum phenomena can be more efficiently captured by investing in stocks that have performed well in past four lagged quarters and selling those that have performed poorly. However, it should be emphasized that to ensure comparability between my strategies, the 2:12 momentum portfolio here is built based on average returns of given months and not according to cumulative returns, like is more traditional. The effect of this choice, justified in the Methodology section, is analysed further in this Thesis.

Short term reversal indeed seems to have a strong effect on the explanatory power of past one year returns to stock performance. W-L portfolio based on full past one-year returns has a t-value of 3.6 while a portfolio excluding the most recent past month has 5.0, while the difference in average returns is 32 basis points monthly. The magnitude is not unheard of in the literature, but proves the need of separating full-one-year returns from the traditional momentum portfolio in this analysis. Albeit large, the effect of short term reversal alone does not explain the difference between past-one-year and quarterend portfolios as the latter continues to outperform even if the most recent past month is left out.

It is notable, that the portfolio formed based on three latest quarterly lags also performs considerably better that one formed with non-quarterend months. The quarterly seasonality indeed seems to be a significant force also separately from annual seasonality researched by Heston and Sadka (2008) and Keloharju et al. (2016) also in traditional momentum. The three-quarterend portfolio also holds larger t-value, implying a larger Sharpe-ratio, than the 2:12 portfolio! This holds in both value and equal weighted portfolios. I consider this to be one of the most interesting findings of my thesis.

As previously noted by Heston and Sadka, the twelfth lag alone appears to be responsible for a huge part of the returns full one-year lag. Like in their results, the t-value of the lagged 12th month portfolio surpasses that of the full one-year strategy (5.1 against 3.6 in value weighted portfolios) in Table 1. Even after removing the effect of short-term reversal, the first annual lag alone yields equal t-value in value weighted and larger in equal weighted portfolios. Twelfth lag alone, however, is surpassed by the four- and three-quarterend portfolios of the first year.

As I consider these results concerning the traditional momentum important for my Thesis and also interesting for potential future research, I decided to form event test similar to those of quarterend strategies presented earlier in this thesis. Table 6 holds returns and t-statistics of even and non-event portfolios constructed identically to those of Table 4. Only the results from value weighted portfolios are presented.

Table 6 - Portfolios controlling firm-specific events for strategies based on intermediate-term past returns

In a given month *t*, U.S. stocks that have returns reported in CRSP database and event-specific information available in CRSP/Compustat are grouped into ten portfolios based on their past performance, top decile belonging to winner (W) and low decile to loser (L) portfolios. The strategies are named based on the lagged returns on which their returns are based, *2:12* being the "traditional momentum" strategy of the past one year excluding the month recent past month. Event (nonevent) portfolios consists of companies that undergo (do not undergo) the said event on month *t*. Only the returns of winners-minus-losers portfolios are presented. They are created every month by subtracting the returns of losers from winners. Portfolios are updated monthly and average value weighted returns (in percent) and t-statics (in brackets) of event and nonevent portfolios are calculated from October 1976 to December 2016 (483 months).

	Earnings announcement		**Dividend announcement**		**Ex dividend day**		**All events**	
Strategy	event	nonevent	event	nonevent	event	nonevent	event	nonevent
2:12	0.92%	0.83%	0.92%	0.87%	0.62%	1.01%	0.44%	0.96%
	[2.4]	[2.6]	[3.0]	[2.6]	[1.9]	[3.1]	[1.1]	[2.4]
3,6,9,12	1.05%	1.06%	1.11%	1.16%	1.03%	1.08%	1.04%	1.00%
	[3.2]	[3.9]	[4.4]	[4.1]	[3.8]	[4.0]	[3.8]	[3.4]
2,4,5,7,8,10,11	0.24%	0.54%	0.33%	0.36%	0.14%	0.50%	0.05%	0.59%
	[0.7]	[1.9]	[1.2]	[1.2]	[0.5]	[1.7]	[0.1]	[1.7]
3,6,9	1.00%	0.97%	0.88%	1.00%	0.94%	0.93%	0.66%	1.08%
	[3.0]	[3.6]	[3.5]	[3.6]	[3.4]	[3.4]	[2.0]	[3.1]
12	0.42%	0.53%	0.34%	0.52%	0.36%	0.42%	0.25%	0.25%
	[1.4]	[2.2]	[1.5]	[2.2]	[1.4]	[1.9]	[0.9]	[0.9]

Again, when interpreting the results, one should keep in mind that in general the event portfolios have fewer companies than their nonevent peers, leading to higher expected standard errors and thus to smaller t-values, with the exception of *All events* strategies where the number of event undergoing and non-undergoing companies is closely comparable.

The results of Table 6 are quite well in line with those of Tables 4 and 5. Apart from the nonevent portfolio of the All events strategy, quarterend portfolio outperforms its peers.

Interestingly, both the event and nonevent portfolios based on entirely to the first annual lag perform considerably worse compared to their Table 5 counterpart. This seems also to have further effect, as a strategy based on the returns of first three quarters has returns comparable to those of full quarterend portfolio. This remarkable finding craves for further research beyond this thesis. Not surprisingly, all *2:12* and *2,4,5,7,8,10,11* portfolios beat their Table 4 *All* and *Non-quartered* counterparts, which is yet another example of the power of the short-term return reversal.

5.6.Returns through the calendar year

To further analyse the performance of my value weighted quarterend strategies, I have dividend the 71-year return history of my portfolios based on individual calendar months. Similar analysis was done by Heston and Sadka (2008). Average returns and t-statistics are presented in Table 7. For example, the column *Jan* of the *Year 1* shows the average January performance of the *W-L* portfolio based on most recent four quarters.

Compared to the W-L portfolios on the Table 1, the average monthly returns presented here often lack significance. This, however, is the results of a sample size one twelfth of the original, leading to smaller t-values categorically. As can be expected by the previous literature on the effect of past returns (e.g. Jegadeesh and Titman (1993), the *Year 1* quarterend portfolio has (insignificant) negative average returns in January. All other months of the strategy are positive, most of them significantly. The strategy earns its highest returns in June and December that are, conveniently, also end-months of *seasonal* quarters. This is likely a coincidence as December is traditionally good month for momentum and neither March nor September show abnormally high returns.

All in all, the effect of January seems small in my results. Excluding the first individual year portfolios, the January returns are very close to the average performance of the strategy, even exceeding that in the Years 16-20 portfolio. This is probably caused by my exclusion of stocks priced less than $5 USD and the chosen weighting methodology, as Conrad and Kaul (1993) noticed small stocks to affect heavy into long-term return reversal. Little common denominators seem to emerge when observing the table. This proves that the quarterly seasonality is not tied to any particular calendar period but abnormal returns seem to be achievable almost around the year. This finding is viable, as it makes investment to quarterend strategies considerably more practical.

Table 7 - Returns of quarterend portfolios in individual calendar months

In a given month *t*, U.S. stocks reported in CRSP database are grouped into ten portfolios based on their past performance, top decile belonging to winners (W) and low decile to loser (L) portfolios. For example, the Year 1 strategy is based on returns of months *t-3*, *t-6*, *t-9* and *t-12*. Only the returns of winners-minus-losers portfolios are presented. They are created every month by subtracting the returns of losers from winners. Portfolios are updated monthly; stocks are value weighted and average returns (in percent) and t-statics (in brackets) are shown individually for all calendar months. Returns calculation period extends from January 1946 to December 2016 (852 months).

Strategy	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Year 1	-0.20%	1.95%	1.14%	1.01%	1.18%	2.07%	0.22%	1.17%	1.12%	1.18%	1.76%	2.42%
	[-0.3]	[2.6]	[2.4]	[1.7]	[2.3]	[4.6]	[0.4]	[2.4]	[1.9]	[2.2]	[2.5]	[4.0]
Year 2	-0.18%	0.26%	0.63%	-0.22%	0.62%	0.82%	0.48%	-0.01%	0.54%	0.61%	1.05%	-0.02%
	[-0.3]	[0.4]	[1.5]	[-0.5]	[1.7]	[2.0]	[1.3]	[0.0]	[1.2]	[1.2]	[1.7]	[-0.1]
Year 3	-0.08%	0.10%	0.09%	0.19%	0.84%	0.17%	0.32%	0.52%	0.28%	-0.19%	1.68%	0.41%
	[-0.2]	[0.2]	[0.3]	[0.5]	[2.1]	[0.5]	[0.7]	[1.4]	[0.5]	[-0.4]	[3.7]	[1.2]
Year 4	0.44%	0.95%	0.38%	-0.44%	0.53%	0.19%	-0.52%	1.17%	0.99%	0.03%	0.97%	0.60%
	[1.0]	[1.7]	[1.0]	[-1.3]	[1.4]	[0.6]	[-1.6]	[3.5]	[2.0]	[0.1]	[1.9]	[1.3]
Year 5	0.32%	0.60%	0.13%	0.23%	-0.27%	1.23%	0.75%	-0.40%	0.15%	0.47%	0.23%	0.31%
	[0.7]	[1.3]	[0.4]	[0.7]	[-0.7]	[3.1]	[2.2]	[-1.1]	[0.3]	[1.1]	[0.4]	[0.8]
Years 6-10	0.73%	0.85%	0.23%	0.57%	0.54%	0.83%	1.39%	0.68%	0.24%	0.80%	1.20%	0.70%
	[1.6]	[1.4]	[0.6]	[1.5]	[1.4]	[2.3]	[3.0]	[1.8]	[0.6]	[1.8]	[2.1]	[2.0]
Years 11-15	0.34%	0.75%	0.31%	-0.41%	0.57%	0.50%	0.67%	0.46%	0.29%	0.19%	1.60%	0.08%
	[0.9]	[2.1]	[0.9]	[-1.2]	[1.4]	[1.4]	[2.1]	[1.2]	[1.0]	[0.5]	[3.8]	[0.2]
Years 16-20	0.85%	0.25%	-0.12%	-1.03%	0.58%	0.17%	0.15%	0.74%	-0.09%	0.63%	1.19%	0.18%
	[1.7]	[0.5]	[-0.4]	[-3.0]	[1.6]	[0.5]	[0.4]	[2.2]	[-0.2]	[1.5]	[2.8]	[0.4]

6. Discussion

Although my results are reviewed in their respective sections, here I will further discuss my findings and the phenomena of quarterly seasonality. I will firstly analyse whether the hypotheses stated earlier in this Thesis can be proven correct by my analysis, address some limitations of my study and compare my findings to previous in the field of the effect of past returns. I will then dedicate a subchapter on possible reasons for the phenomena, concentrating on firm-specific events and finally briefly tackle the potential practical barriers of exploiting the quarterly seasonality phenomena.

6.1.Confirming hypotheses and additional robustness checks

The results confirm Hypothesis 1. Investing in stocks based on their lagged quarterend returns is more profitable than based on their past performance in general. This holds in all eight formation intervals up to 20 years, as can be seen in Table 1. The spread in average returns between zero-investment strategies based on quarterend lagged months and all lagged months of the most recent past year is 47 basis points monthly. This spread is considerably large compared to monthly profits of all-lags strategy, 78 basis points monthly. Quarterend strategies also have larger t-value than their peers. The effect of quarterly seasonality cannot be solely explained by the annual seasonality studied by my predecessors, as can be seen in Table 2. The nonannual quarterend strategies continue to outperform strategies based on all lagged months in every portfolio formation interval. The quarterly seasonality effect is weaker in equally weighted portfolios (Table 3) but still yield significantly positive returns in strategy based on most recent four quarterend lags.

Hypothesis 2 states that investing in stocks based on their returns of the most recent four quarters is more profitable than following a traditional momentum strategy taking into account past returns from 2 to 12-month period. Indeed, the average returns of a quarterend strategy based on the most recent past year exceeds those of traditional momentum portfolio by 15 basis points monthly (1.8% yearly) and also has a higher t-value. Notably, the strategy investing based on the returns of most recent three quarters has a t-value higher that the of the traditional momentum portfolio, implying larger Sharpe-ratio (Sharpe (1994). The results hold in both value weighted and equal weighted portfolios.

We can also confirm Hypothesis 3 based on my results. The quarterend months do not seem to contribute to long-term return reversal phenomenon. Strategies based on quarterend months remain significantly positive on the formation intervals of past two to five years. The average returns remain positive, although insignificant after the most recent lagged year when the annual lags are removed from the analysis. When addressing this finding, it should be remembered that I have excluded stocks priced smaller than $5 USD from my data. These stocks were found by Conrad and Kaul (1993) to have an effect to long-term reversal phenomena, but their exclusion was a decision influenced by many of my predecessors studying the effect of past returns (e.g. Jegadeesh and Titman (2001). However, my chosen valuation methodology of value weighting should reduce the effect of these "penny stocks" and thus increase the robustness of my results related to Hypothesis 3.

I decided to use dividend excluded returns in my analysis as I initially feared dividends to create autocorrelation in my data when studying the effect of past quarterly returns. In retrospect, this fear was most likely without ground. As a robustness check, I formed a quarterend strategy based on the most recent past year also with dividend-included returns and delisting returns data (full results unreported). The average returns ceteris paribus of the winners-minus-losers portfolio including dividends is 1.03% monthly (t-value 6.1) which is less than for a strategy excluding dividend from Table 1 yielding 1.25% monthly (t-value 7.3). The return difference is caused by higher performance of all decile portfolios with divided-included data, leading into smaller returns of winners-minus-losers portfolio. I have little reason to doubt that with divideds-included data, my results of winners-minus-losers portfolios would be smaller across all strategies but do not see that this would endanger my results altogether.

My portfolios are formed based on average returns of given months, as majority of my strategies are based on non-continuous lags. Because of comparability, average weighting was also used in portfolios based on continuous months, including the traditional momentum. As momentum portfolios are often based on cumulative returns, it could be questioned whether the portfolio based on quarterend months outperforms the traditional momentum based on cumulative returns. My Year 1 quarterend portfolio has average returns of 1.25% (t-value 7.3) while the portfolio based on past months 2:12 has 1.10% (t-value 5.1) during a period from 1946 to 2016. During a similar period, momentum portfolio based on cumulative returns published in the data library of Kenneth French earns on average 0.71% (t-value 5.4) monthly. Although this portfolio is not compeletely comparable to my results as it uses breaking points of 3rd decile and 7th decile to define winners and losers and is actually based on the returns of several momentum portfolios of different size groups, it can be safely stated that the returns of Year 1 quarterend strategy are more than competitive when compared to traditional momentum strategies.

My equally weighted returns are considerably less significant than value weighted ones. Speculatively, this might be the reason why Heston and Sadka, whose prime returns were equally weighted, did not comment on the quarterly pattern in their results. The smaller returns of equally weighted zero-investment portfolios are resulted by the better performance of equal weighted decile portfolios overall: Every single equally weighted decile portfolio presented in this work has higher average monthly return than its value weighted counterpart. This finding makes sense as small stocks have been found to have larger average returns (e.g. Banz (1981). The standard errors are also smaller in equally weighted portfolios which is reasonable as companies of extremely large size can have substantial effect to value weighted strategies. It is unclear, however, whether this effect alone explains the weaker returns of winners-minus-losers portfolios of equally weighted strategies. Table I of Appendix can be used to further investigate the difference. Table I includes only companies that have a market capitalization larger than NYSE median. All average returns of quarterend W-L strategies of the large-company sample in Table I are significantly positive and within 15 basis points from their whole-sample counterparts from Table 1 and the median spread is positive. This observation suggests that the small stock may indeed be behind the lower average returns. The finding is interesting and craves for further research beyond this thesis.

Straightforward comparison between my results and ones of Heston and Sadka (2008) is difficult because of differences in data and methodology. Heston and Sadka used data from 1945 to 2002 consisting 58 years, whereas I used the full existence of CRSP database from 1926 to 2016, or 91 years, in my results excluding the event studies. My predecessors also used portfolio formation intervals distributed more evenly in the examination period extending to lagged 20 years, whereas I concentrated on the intermediate horizon. Another key difference is that Heston and Sadka used equal weighted returns as a base of their analysis when I used mainly value weighting although I also included equal weighted portfolios for comparison. My predecessors did not mention removing stocks priced less than \$5 USD, so they were presumably kept in the analysis while I excluded them. Comparing my returns of *All* portfolios from Table 1 to Heston and Sadka's results is the best available comparison between these two works. Our results from winners-minus-losers portfolios are well in line when taking into account the differences in data and methodology. If anything, Heston and Sadka's results are larger in magnitude: Both the average returns of Year 1 portfolio are higher and the returns on longer formation intervals lower than mine. They are also considerable differences in the results of event control tests, which will be addressed further in this chapter.

Novy-Marx claims in his 2012 study that the returns of past seven to twelve months are mainly responsible for the momentum returns. The findings of my study do not fully support his results. Although the twelfth lag undoubtedly holds a huge effect to momentum and there is significant short-term reversal phenomenon, I find no other evidence of clear differences in autocorrelations between the short and long horizon months of the traditional momentum. De Bondt and Thaler (1985) found the return reversal effect to affect more significantly to past losers than to winners. When analysing my results of the decile portfolios of nonannual quarterend strategies, similar effect can be found. Loser portfolios of the portfolio formation intervals of Year 2 to Year 5 are higher or equal than the average returns of decile portfolios of the interval in question. This effect is considerably weaker in full quarterend portfolios, but the returns of loser portfolios are still close to median returns of the decile portfolios in intervals accosiated with the long-term return reversal phenomena.

6.2. Causes of quarterly seasonality

I tested the effect of several company specific events to identify possible causes of the quarterly seasonality pattern I had found. The effect of earnings announcements, dividend announcements and ex-dividend dates were all tested individually in the spirit of Heston and Sadka (2008). In addition, I also tested the pooled effect of these events with a combined dataset. None of the individual events nor their combination seems to explain the quarterly seasonality phenomena but the strategies continue to outperform others in both event and nonevent portfolios in almost all the cases. This was a surprise for me, as I thought that events, and especially quarterly earnings announcements, would have played an important role in explaining the remarkable quarterend pattern.

The results of these event portfolios of earnings announcements were also particularly bewildering, and even seemed implausible at first glance when comparing to results obtained by previous literature. For example, the spread between earnings announcement event and nonevent portfolios' average returns of the Year 1 *All* strategy differs from what Heston and Sadka (2008) reported. I see three potential reasons for this difference besides mistake of either me or my predecessors: My chose to exclude stocks priced lower than $5 USD, our differences in portfolio weighting methodology and the difference in time periods of returns calculation. Heston and Sadka calculate portfolio returns from January 1965 to December 2002 while I calculate the returns of event portfolios from October 1976 to December 2016. This leaves 315 historical months where our time periods intersect, compared to my total of 483 months of returns calculation.

The differences in portfolio weighting methodology and time period of return calculation are my prime suspects. To test their effect, I calculated the average returns of equally weighted event portfolios (unreported) from October 1976 to December 2002. Unfortunately, I could not extend my portfolio formation period all the way to Heston and Sadka's starting point, 1965 because of data limitations of Compustat. Here I am particularly interested in the results of strategies based on all lagged months, as those portfolios are comparable to Heston and Sadka's results. The average returns of earnings announcement event portfolio based on all months of the most recent past year was 0.93% (t-value 2.4) and nonevent 0.47% (t-value 1.3). The values differ remarkably from my prime results gained using value weighting methodology and a time period exceeding to December 2016. Further analysis unveils that this difference seems to originate from both the weighting method and the time period, as value weighted returns of event portfolio are already larger than that of their nonevent peer's when the time frame is limited to December 2002, but the difference is smaller than in the case of equal weighted results.

It is thus proven that the weighting methodology and different time frame is, at least partly, behind the differences between mine and Heston and Sadka's event portfolio results. My average equal weighted returns from October 1976 to December 2016 are smaller in magnitude than the returns got by Heston and Sadka, 2.19% (6.15) for event months and 1.22% (4.20) for nonevent months, but more comparable than my prime results. It comes as to no surprise that equal weighted earnings announcement event portfolios perform better than their value weighted peers as the post earnings announcement drift affects most heavily on small stocks (e.g. Chari, Jagannathan and Ofer (1988). However, it is interesting how the difference between event and nonevent earnings announcement portfolios seemed to dilute after 2002. Indeed, the average returns of the 14-year period of 2003-2016 for event and nonevent earnings announcement Year 1 *All* portfolios were -0.34% and 0.30%, respectively. Companies that did not undergo earnings announcement in a given month outperformed those that did on a clear margin, on the contrary what one would expect based on previous literature. This interesting finding claims for further investigation out of the scope of this work.

Besides firm-specific events of the fiscal year, little credible explanations for the quarterly seasonality phenomenon comes to mind. The pattern is strong and robust and although it seems to have low returns in January, like many of the strategies based on past returns do, it is quite persistent across the calendar year. Institutional trading might partly explain quarterly seasonality as it has proven to have a price impact (e.g. Sias, Starks and Titman (2001) and behaviours like window dressing might contribute to quarterly trading patterns. It is hard to believe, however, that these patterns alone would be behind the quarterly seasonality. Controlling for stock institutional ownership could produce interesting results but is unfortunately outside the scope of my work. It would be also interesting to further investigate the effect of company market capitalization to quarterly seasonality, as my equal weighted returns in Table 3 are considerably weaker than value weighted in Table 1. Further analysis on the matter could help to explain the quarterly pattern.

6.3.Practical implementation of the strategy

Although the prime perspective of this Thesis is not to present a practical, profit-earning strategy, I think it is important, even if shortly, to address the potent limitations of exploitation of the quarterend pattern that I have discovered. I have discovered a powerful pattern in U.S. stock markets: winners-minus-losers i.e. zero investment portfolios based on quarterend months yield significantly positive profits. However, in practice certain barriers and market inefficiencies can obstruct the exploitation of my results, most important of them being trading costs, price impact of trade, illiquidity and potential difficulties of short sale.

All strategies presented in this Thesis have a portfolio holding period of one month. Like all strategies based on past returns, quarterend strategies demand considerable upkeeping leading into trading fees. As the strategies are based on past returns of non-continuous months, they presumably demand even more trading activity compared to, for example, traditional momentum strategies. However, the profits of the strategies are considerable: winners-minus-losers portfolio based on the returns of the last four quarterend months yield on average 1.25% monthly (16.10% yearly) and thus should remain profitable after taking into account modest trading expenses.

Sufficient liquidity and the price impact of trade is another concern in all stock dealing strategies. This obstacle has only limited affect to my portfolios as they have been shown to excel when value weighted. Weighting stocks accepted to portfolio based on their market capitalization emphasizes large companies that are more likely to have liquid, much traded securities. Large market cap also decreases the price impact. For example Korajczyk and Sadka (2004) noted that value weighted strategies tend to perform better after taking into account transaction costs and the price impact of trade. Restricting stocks priced under $5 USD, like I have done in all strategies of this work, will further increase the liquidity of the strategy.

Although one could only invest to winner portfolio of quarterend strategy (and profit quite handsomely), strategies of most concern presented in this Thesis are zero-investment in nature. This implies, that an investor must commit to shares borrowing i.e. short stocks to follow them. Short selling is both legal and extremely popular in U.S.; Diether, Lee and Werner (2008) find short sales to constitute 24% of share volume in NYSE. In despite of this, share loan fees vary tremendously. Diether (2008) investigated U.S. short selling contracts from 1999 to 2005 and reported that while the median fee was 2.45% p.a., 25th and 75th percentiles were 0.16% and 5.19% p.a., respectively. However, short selling fee was found to be strongly inversely related to market cap, large-cap stocks having low fees. Again my choice of portfolio valuation method and “penny stock” restrictions will limit the encumbrance of these fees in my strategies.

Not only being both technically and practically viable, quarterend strategies are also simple: ranking stocks based on their average returns of past quarterend months does not demand complex modelling or investment analysis and neither does building value weighted portfolios based on this ranking. The practical implementation of, for example, the Year 1 quarterend strategy is also supported by the fact that the profits are distributed quite evenly around the year, January being the only month with negative average profits as can be observed from the Table 7. This further simplifies the investment procedure and one can justifiable argue that, beyond the cost of transactions and short sale, quarterend strategies can be executed quite affordably.

7. Conclusion

In this Master's Thesis I have research the previously undiscovered stock market phenomenon of quarterly seasonality, related to the explanatory power of past returns to stock price. I found that security's expected performance in a given month *t* is correlated with its returns in lagged quarterend months i.e. months *t-3,6,9,…*. I formed monthly updated stock trading strategies based on returns of quarterend lagged months and compared them to strategies based on returns of all lags and non-quarterend lags. The quarterend strategies beat other strategies in all tested formation intervals.

The differences in portfolio returns were notable. A value weighted zero-investment strategy based on the returns of quarterend lags of the most recent past year yields on average 1.25% monthly (16.10% yearly) during the investment period of 852 months from 1946 to 2016, while a strategy based on non-quarterend lags has an average returns of 0.25% during the same period. This pattern is not limited to the most recent past year, but the returns of zero-investment quarterend strategies remain significantly positive in every tested portfolio formation interval up to lagged 20 years.

The returns of these portfolios cannot be full explained by the strong correlation of annual lagged returns (months *t-12,24,36,…*) to stock price. Strategies based on nonannual quarterend lags still outperformed strategies based on all months in every interval. The returns of nonannual quarterend strategies based on the returns of lagged years 2-5 had positive, although insignificant, returns implying that past quarterend months do not contribute to long-term reversal phenomenon. The equally weighted returns of quarterend winners-minus-losers portfolios were considerably smaller than their value weighted peers, originating from the better relative performance of losers portfolios.

Quarterend strategy based on the most recent past year was found to be more lucrative yet less risky than the traditional momentum strategy based on returns of months *t-2:12*. This finding is remarkable. In pure asset management sense, it seems to be more profitable to invest on quarterend strategy rather than on a strategy based on the average returns of past year, even after the negatively correlated most recent month has been left out from the analysis. The finding may also help us to better understand the underlying forces behind one of the most puzzling anomalies of the asset management literature. Interestingly, a nonannual quarterend strategy also had higher t-value than the traditional momentum strategy, implying again that this quarterend patterns cannot be fully explained by the annual seasonality phenomenon. The performance of quarterend strategies could not be explained by firm-specific events of the fiscal year. Controlling for earnings announcements, dividend announcements or ex-dividend dates did not diminish the superiority of quarterend portfolios neither when tested individually nor with an event-combined dataset. Returns of quarterend strategies were also not tied to any particular calendar month, although the returns of a strategy based on most recent four quarters performed poorly on January and particularly well in December.

I was unable to find the origins of the quarterly seasonality phenomena in my research. This should be, in my opinion, the fundamental goal for any further research on the subject. Robustness checks on the returns could be widened to include industries and the effect of market capitalization could be research further perhaps by dividing companies into different size groups. Controlling for institutional trading would help to identify the possible effect of window dressing to the phenomena. The decision for excluding stocks priced less than $5 USD could be questioned and its effect tested. Event controlling tests could be widened still. It would also be interesting to examine whether my results hold in markets outside U.S.

I am more than satisfied with the outcome of my Master's Thesis. The journey of making this work has been the most arduous of my life, but at the same time both tremendously educational and rewarding. After standing on the shoulders of so many giants, my hope is that this Thesis could provide something to its reader, were it data or an inspiration for future research.

8. References

Aharony, J. and Swary, I., 1980. Quarterly dividend and earnings announcements and stockholders' returns: An empirical analysis. *The Journal of Finance*, *35*(1), pp.1-12.

Ariel, R.A., 1987. A monthly effect in stock returns. *Journal of financial economics*, *18*(1), pp.161-174.

Asness, C.S., Moskowitz, T.J. and Pedersen, L.H., 2013. Value and momentum everywhere. *The Journal of Finance*, *68*(3), pp.929-985.

Ball, R. and Brown, P., 1968. An empirical evaluation of accounting income numbers. *Journal of accounting research*, pp.159-178.

Banz, R.W., 1981. The relationship between return and market value of common stocks. *Journal of financial economics*, *9*(1), pp.3-18.

Barberis, N., Shleifer, A. and Vishny, R., 1998. A model of investor sentiment1. *Journal of financial economics*, *49*(3), pp.307-343.

Beaver, W.H., 1968. The information content of annual earnings announcements. *Journal of accounting research*, pp.67-92.

Bernard, V.L. and Thomas, J.K., 1990. Evidence that stock prices do not fully reflect the implications of current earnings for future earnings. *Journal of Accounting and Economics*, *13*(4), pp.305-340.

Berument, H. and Kiymaz, H., 2001. The day of the week effect on stock market volatility. *Journal of economics and finance*, *25*(2), pp.181-193.

Bessembinder, H. and Zhang, F., 2014. Predictable corporate distributions and stock returns. *The Review of Financial Studies*, *28*(4), pp.1199-1241.

Boehme, R.D. and Sorescu, S.M., 2002. The Long-run Performance Following Dividend Initiations and Resumptions: Underreaction or Product of Chance?. *the Journal of Finance*, *57*(2), pp.871-900.

Brav, A., Geczy, C. and Gompers, P.A., 2000. Is the abnormal return following equity issuances anomalous?. *Journal of Financial Economics*, *56*(2), pp.209-249.

Chang, T.Y., Hartzmark, S.M., Solomon, D.H. and Soltes, E.F., 2017. Being surprised by the unsurprising: Earnings seasonality and stock returns. *The Review of Financial Studies*, *30*(1), pp.281-323.

Chari, V.V., Jagannathan, R. and Ofer, A.R., 1988. Seasonalities in security returns: The case of earnings announcements. *Journal of Financial Economics*, *21*(1), pp.101-121.

Conrad, J. and Kaul, G., 1993. Long-Term Market Overreaction or Biases in Computed Returns?. *The Journal of Finance*, *48*(1), pp.39-63.

Cooper, M., 1999. Filter rules based on price and volume in individual security overreaction. *The Review of Financial Studies*, *12*(4), pp.901-935.

Cross, F., 1973. The behavior of stock prices on Fridays and Mondays. *Financial analysts journal*, *29*(6), pp.67-69.

Daniel, K., Hirshleifer, D. and Subrahmanyam, A., 1998. Investor psychology and security market under-and overreactions. the Journal of Finance, 53(6), pp.1839-1885.

Daniel, K. and Moskowitz, T.J., 2016. Momentum crashes. *Journal of Financial Economics*, *122*(2), pp.221-247.

De Bondt, W.F. and Thaler, R., 1985. Does the stock market overreact?. *The Journal of finance*, *40*(3), pp.793-805.

Diether, K., 2008. Short selling, timing, and profitability. *Unpublished working paper, The Ohio State University*.

Diether, K.B., Lee, K.H. and Werner, I.M., 2008. Short-sale strategies and return predictability. *The Review of Financial Studies*, *22*(2), pp.575-607.

Erb, C.B. and Harvey, C.R., 2006. The strategic and tactical value of commodity futures. *Financial Analysts Journal*, *62*(2), pp.69-97.

Fama, E.F. and French, K.R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, *33*(1), pp.3-56.

Fama, E.F. and French, K.R., 1996. Multifactor explanations of asset pricing anomalies. *The journal of finance*, *51*(1), pp.55-84.

Fama, E.F. and MacBeth, J.D., 1973. Risk, return, and equilibrium: Empirical tests. *Journal of political economy*, *81*(3), pp.607-636.

Ferris, S.P., Noronha, G. and Unlu, E., 2010. The more, the merrier: An international analysis of the frequency of dividend payment. *Journal of Business Finance & Accounting*, *37*(1-2), pp.148-170.

Foster, G., Olsen, C. and Shevlin, T., 1984. Earnings releases, anomalies, and the behavior of security returns. *Accounting Review*, pp.574-603.

Griffin, J.M., Ji, X. and Martin, J.S., 2003. Momentum investing and business cycle risk: Evidence from pole to pole. *The Journal of Finance*, *58*(6), pp.2515-2547.

Grinblatt, M. and Moskowitz, T.J., 1999. Do industries explain momentum. *The Journal of Finance*, *54*(4), pp.1249-1290.

Grinblatt, M. and Moskowitz, T.J., 2004. Predicting stock price movements from past returns: The role of consistency and tax-loss selling. *Journal of Financial Economics*, *71*(3), pp.541-579.

Harris, L., 1986. A transaction data study of weekly and intradaily patterns in stock returns. *Journal of financial economics*, *16*(1), pp.99-117.

Hartzmark, S.M. and Solomon, D.H., 2013. The dividend month premium. *Journal of Financial Economics*, *109*(3), pp.640-660.

Hartzmark, S.M. and Solomon, D.H., 2017. Recurring Firm Events and Predictable Returns: The Within-Firm Time-Series. *Annual Review of Financial Economics*, Forthcoming. Available at SSRN: https://ssrn.com/abstract=3053015

Heston, S.L. and Sadka, R., 2008. Seasonality in the cross-section of stock returns. *Journal of Financial Economics*, *87*(2), pp.418-445.

Heston, S.L. and Sadka, R., 2010. Seasonality in the cross section of stock returns: the international evidence. *Journal of Financial and Quantitative Analysis*, *45*(5), pp.1133-1160.

Hong, H. and Stein, J.C., 1999. A unified theory of underreaction, momentum trading, and overreaction in asset markets. *The Journal of finance*, *54*(6), pp.2143-2184.

Jegadeesh, N., 1990. Evidence of predictable behavior of security returns. *The Journal of finance*, *45*(3), pp.881-898.

Jegadeesh, N. and Titman, S., 1993. Returns to buying winners and selling losers: Implications for stock market efficiency. *The Journal of finance*, *48*(1), pp.65-91.

Jegadeesh, N. and Titman, S., 2001. Profitability of momentum strategies: An evaluation of alternative explanations. *The Journal of finance*, *56*(2), pp.699-720.

Johnson, T.C., 2002. Rational momentum effects. *The Journal of Finance*, *57*(2), pp.585-608.

Keloharju, M., Linnainmaa, J.T. and Nyberg, P., 2016. Return seasonalities. *The Journal of Finance*, *71*(4), pp.1557-1590.

Kho, B.C., 1996. Time-varying risk premia, volatility, and technical trading rule profits: Evidence from foreign currency futures markets. *Journal of Financial Economics*, *41*(2), pp.249-290.

Korajczyk, R.A. and Sadka, R., 2004. Are momentum profits robust to trading costs?. *The Journal of Finance*, *59*(3), pp.1039-1082.

Lakonishok, J. and Smidt, S., 1988. Are seasonal anomalies real? A ninety-year perspective. *The review of financial studies*, *1*(4), pp.403-425.

Loughran, T. and Ritter, J.R., 1995. The new issues puzzle. *The Journal of finance*, *50*(1), pp.23-51.

Loughran, T. and Vijh, A.M., 1997. Do long-term shareholders benefit from corporate acquisitions?. *The Journal of Finance*, *52*(5), pp.1765-1790.

McLean, R.D. and Pontiff, J., 2016. Does academic research destroy stock return predictability?. *The Journal of Finance*, *71*(1), pp.5-32.

Michaely, R., Thaler, R.H. and Womack, K.L., 1995. Price reactions to dividend initiations and omissions: Overreaction or drift?. *The Journal of Finance*, *50*(2), pp.573-608.

Moskowitz, T.J., 2010. Explanations for the momentum premium. *A white paper by AQR Capital Management*, Summer 2010.

Moskowitz, T.J., Ooi, Y.H. and Pedersen, L.H., 2012. Time series momentum. *Journal of financial economics*, *104*(2), pp.228-250.

Novy-Marx, R., 2012. Is momentum really momentum?. *Journal of Financial Economics*, *103*(3), pp.429-453.

Rouwenhorst, K.G., 1998. International momentum strategies. *The Journal of Finance*, *53*(1), pp.267-284.

Rouwenhorst, K.G., 1999. Local return factors and turnover in emerging stock markets. *The journal of finance*, *54*(4), pp.1439-1464.

Savor, P. and Wilson, M., 2016. Earnings announcements and systematic risk. *The Journal of Finance*, *71*(1), pp.83-138.

Sharpe, W.F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, *19*(3), pp.425-442.

Sharpe, W.F., 1966. Mutual fund performance. *The Journal of business*, *39*(1), pp.119-138.

Sharpe, W.F., 1994. The sharpe ratio. *Journal of portfolio management*, *21*(1), pp.49-58.

Sias, R.W., Starks, L.T. and Titman, S., 2001. The Price Impact of Institutional Trading. Available at SSRN: https://ssrn.com/abstract=283779

Subrahmanyam, A., 2005. Distinguishing Between Rationales for Short-Horizon Predictability of Stock Returns. *Financial Review*, *40*(1), pp.11-35.

Thaler, R.H., 1987. Anomalies: the January effect. *Journal of Economic Perspectives*, *1*(1), pp.197-201.

Wachtel, S.B., 1942. Certain observations on seasonal movements in stock prices. *The journal of business of the University of Chicago*, *15*(2), pp.184-193.

Watts, R., 1973. The information content of dividends. *The Journal of Business*, *46*(2), pp.191-211.

9. Appendix

Table I – Large cap portfolios based on past returns

In a given month *t*, U.S. stocks reported in CRSP database that have a market capitalization larger than NYSE median are grouped into ten portfolios based on their past performance, top decile belonging to winner (W) and low decile to loser (L) portfolios. For example, the Quarterend strategy of Year 1 is based on returns of months *t-3*, *t-6*, *t-9* and *t-12* while the All strategy of the same interval is based on months from *t-1* to *t-12*. Winners-minus-losers portfolio (W-L) is created every month by subtracting the returns of losers from winners. Portfolios are updated monthly and average value weighted returns (in percent) and t-statics (in brackets) of all strategies are calculated from January 1946 to December 2016 (852 months).

Strategy		**W**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**L**	**W-L**
	All	1.10%	0.89%	0.76%	0.69%	0.51%	0.57%	0.44%	0.48%	0.45%	0.50%	0.60%
		[5.1]	[4.9]	[4.5]	[4.2]	[3.2]	[3.4]	[2.7]	[2.8]	[2.4]	[2.2]	[2.9]
Year 1	Quarterend	1.19%	0.98%	0.86%	0.69%	0.63%	0.57%	0.48%	0.44%	0.36%	0.08%	1.11%
		[5.6]	[5.4]	[5.0]	[4.3]	[4.0]	[3.5]	[3.0]	[2.6]	[1.9]	[0.4]	[6.6]
	Non-quarterend	0.83%	0.72%	0.61%	0.59%	0.56%	0.56%	0.60%	0.57%	0.63%	0.74%	0.09%
		[3.9]	[4.1]	[3.5]	[3.6]	[3.4]	[3.6]	[3.7]	[3.4]	[3.4]	[3.4]	[0.5]
	All	0.63%	0.61%	0.48%	0.53%	0.67%	0.48%	0.65%	0.68%	0.86%	0.86%	-0.23%
		[2.9]	[3.3]	[2.8]	[3.2]	[4.0]	[2.9]	[3.7]	[4.1]	[4.7]	[4.3]	[-1.3]
Year 2	Quarterend	0.89%	0.71%	0.67%	0.61%	0.64%	0.53%	0.59%	0.54%	0.53%	0.61%	0.27%
		[4.3]	[3.9]	[3.8]	[3.7]	[3.9]	[3.4]	[3.7]	[3.2]	[3.0]	[3.0]	[2.0]
	Non-quarterend	0.42%	0.47%	0.51%	0.54%	0.47%	0.55%	0.70%	0.79%	0.83%	1.01%	-0.60%
		[2.0]	[2.6]	[3.1]	[3.2]	[2.9]	[3.3]	[4.1]	[4.5]	[4.7]	[5.3]	[-3.8]
	All	0.61%	0.61%	0.60%	0.65%	0.56%	0.53%	0.57%	0.61%	0.66%	0.80%	-0.19%
		[2.8]	[3.2]	[3.4]	[3.8]	[3.3]	[3.2]	[3.4]	[3.6]	[3.8]	[4.2]	[-1.3]
Year 3	Quarterend	0.78%	0.77%	0.67%	0.67%	0.66%	0.52%	0.50%	0.52%	0.41%	0.52%	0.26%
		[3.7]	[4.1]	[3.8]	[4.0]	[4.0]	[3.2]	[3.1]	[3.1]	[2.4]	[2.7]	[2.1]
	Non-quarterend	0.49%	0.51%	0.57%	0.49%	0.55%	0.59%	0.63%	0.67%	0.82%	0.87%	-0.37%
		[2.3]	[2.7]	[3.3]	[2.9]	[3.3]	[3.6]	[3.8]	[3.9]	[4.7]	[4.6]	[-2.6]

Strategy		W	2	3	4	5	6	7	8	9	L	W-L
	All	0.86%	0.76%	0.67%	0.63%	0.68%	0.63%	0.67%	0.60%	0.63%	0.75%	0.10%
		[4.2]	[4.5]	[4.2]	[4.2]	[4.7]	[4.5]	[4.6]	[4.1]	[4.3]	[4.8]	[0.7]
Year 4	Quarterend	0.93%	0.87%	0.82%	0.68%	0.61%	0.63%	0.64%	0.65%	0.50%	0.47%	0.45%
		[4.9]	[5.2]	[5.3]	[4.5]	[4.3]	[4.4]	[4.5]	[4.5]	[3.4]	[2.9]	[3.8]
	Non-quarterend	0.72%	0.66%	0.60%	0.59%	0.58%	0.67%	0.74%	0.71%	0.76%	0.89%	-0.17%
		[3.7]	[3.9]	[3.9]	[4.0]	[3.9]	[4.7]	[5.2]	[4.9]	[5.2]	[5.5]	[-1.3]
	All	0.88%	0.64%	0.77%	0.65%	0.71%	0.53%	0.70%	0.64%	0.63%	0.67%	0.21%
		[4.3]	[3.8]	[5.0]	[4.3]	[4.8]	[3.7]	[5.0]	[4.6]	[4.4]	[4.2]	[1.7]
Year 5	Quarterend	0.88%	0.86%	0.88%	0.81%	0.75%	0.59%	0.52%	0.54%	0.47%	0.43%	0.46%
		[4.7]	[5.4]	[5.6]	[5.5]	[5.3]	[4.2]	[3.6]	[3.7]	[3.1]	[2.6]	[3.9]
	Non-quarterend	0.67%	0.64%	0.63%	0.59%	0.58%	0.58%	0.70%	0.75%	0.83%	0.85%	-0.18%
		[3.4]	[3.9]	[4.1]	[4.0]	[4.0]	[4.1]	[5.0]	[5.2]	[5.7]	[5.4]	[-1.6]
	All	0.75%	0.64%	0.65%	0.63%	0.63%	0.61%	0.77%	0.62%	0.67%	0.80%	-0.04%
		[3.7]	[3.7]	[4.0]	[4.2]	[4.3]	[4.1]	[5.6]	[4.6]	[5.0]	[5.6]	[-0.3]
Years 6-10	Quarterend	0.93%	0.92%	0.80%	0.66%	0.79%	0.73%	0.57%	0.63%	0.38%	0.27%	0.66%
		[4.9]	[5.6]	[5.2]	[4.4]	[5.5]	[5.1]	[4.0]	[4.5]	[2.6]	[1.8]	[5.3]
	Non-quarterend	0.60%	0.48%	0.45%	0.48%	0.61%	0.66%	0.81%	0.83%	0.75%	1.04%	-0.43%
		[3.1]	[2.9]	[2.9]	[3.2]	[4.2]	[4.7]	[5.6]	[6.0]	[5.4]	[7.1]	[-3.2]
	All	0.77%	0.68%	0.70%	0.66%	0.64%	0.61%	0.63%	0.66%	0.64%	0.65%	0.12%
		[4.4]	[4.4]	[4.7]	[4.5]	[4.3]	[4.2]	[4.3]	[4.5]	[4.5]	[4.2]	[1.0]
Years 11-15	Quarterend	0.87%	0.79%	0.78%	0.80%	0.60%	0.56%	0.66%	0.59%	0.47%	0.34%	0.53%
		[5.3]	[5.3]	[5.3]	[5.4]	[4.2]	[3.9]	[4.6]	[4.0]	[3.2]	[2.2]	[5.1]
	Non-quarterend	0.55%	0.60%	0.67%	0.58%	0.66%	0.71%	0.65%	0.68%	0.71%	0.83%	-0.27%
		[3.2]	[3.9]	[4.5]	[3.9]	[4.5]	[4.9]	[4.5]	[4.7]	[4.8]	[5.3]	[-2.5]
	All	0.70%	0.58%	0.73%	0.65%	0.59%	0.65%	0.66%	0.62%	0.56%	0.67%	0.03%
		[4.1]	[3.7]	[4.8]	[4.4]	[4.0]	[4.6]	[4.7]	[4.4]	[4.0]	[4.4]	[0.3]
Years 16-20	Quarterend	0.76%	0.74%	0.73%	0.73%	0.70%	0.69%	0.63%	0.53%	0.37%	0.47%	0.29%
		[4.6]	[4.9]	[5.0]	[5.0]	[4.9]	[4.9]	[4.3]	[3.8]	[2.5]	[2.9]	[2.6]
	Non-quarterend	0.60%	0.66%	0.54%	0.61%	0.54%	0.66%	0.59%	0.68%	0.72%	0.82%	-0.22%
		[3.5]	[4.2]	[3.7]	[4.2]	[3.5]	[4.6]	[4.2]	[4.8]	[5.1]	[5.4]	[-2.0]