Seasonality in the Cross-Section of Stock Returns

Bachelor Thesis

Winter Semester 2017/2018

Submitted to

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Frankfurt am Main, 25.01.2018

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III List of Abbreviations

AMEX	American Stock Exchange
CAPM	Capital Asset Pricing Model
CRSP	Center for Research in Security Prices
DLRET	Delisting return
EXCHCD	Exchange code
HML	High minus low
MGMT	Management related mispricing factor
NYSE	New York Stock Exchange
PERF	Performance related mispricing factor
PERMNO	Permanent identification number
PR	Portfolio return
RET	Return

RF	Risk free rate
RM	Market return
SHRENDDT	Shares observation end date
SMB	Small minus big
WL	Winner-loser

IV List of Symbols

a	regression intercept in risk and mispricing factor models
d	delisting date
dr	delisting return
e	residual of regressions
h	regression coefficient for factor HML
i	stock index
j	portfolio index
k	lag (in months)
ltd	last trading day of the month
m	regression coefficient for factor MGMT
mdr	monthly delisting return
p	regression coefficient for factor PERF
r	stock monthly return
r^*	stock monthly return including delisting return
$\hat{r}$	stock return estimate of cross-sectional regressions of monthly returns
s	regression coefficient for factor SMB
t	time (month)
$\hat{\alpha}$	intercept of cross-sectional regressions of monthly returns
β	regression coefficient for factor RM-RF
$\hat{\gamma}$	regression coefficient of cross-sectional regressions of monthly returns

1 Introduction

This study explores anomalies in stock returns found in their seasonal patterns. These are verified through multiple trading strategies based on past-performance returns that require information up to 20 years in the past. Some of the presented strategies deliver relatively high performance, especially for those strategies based on returns in the same calendar month from past years. In order to minimize any possible bias due to omitted delisting returns, those are incorporated into the monthly returns. Furthermore, to find an explanation for this seasonal effect, behavioral theories are discussed and the returns are controlled for risk and mispricing factors. However, empirical evidence indicates no evidence of explanation based on these factors for the seasonal patterns. Furthermore, possible reasons why the returns persist are discussed.

At the beginning of this thesis, section 2 reviews the concept of a seasonal component, which is later empirically investigated in the context of stock returns. Section 3 presents different strategies based on past-performance returns and results obtained by academic researchers. Possible explanations for the high returns based on these strategies are reviewed in section 4. This is followed by the empirical analysis, which investigates whether some of the presented high returns persist, verify in which periods they are particularly pronounced and explore possible explanations based on risk and mispricing factors. Finally, potential reasons why arbitrageurs do not shrink the high returns are discussed in section 6, followed by the conclusion in section 7.

2 Seasonal Component

Fluctuations on time-series are commonly composed by four elements: trend, cyclical, seasonal and residual components.[1] The trend represents the long-term movement behind the series, the cyclical part stands for the effects caused by cyclical economic situations, such as crises and economic booms. Moreover, the seasonal component is defined as recurrent cyclical changes in time-series that are observed in yearly intervals. Finally, the residual, or irregular component, represents irregular or unique events.[2] The seasonal

[1] Cf. Winker, 2010, p.221f.
[2] Cf. Winker, 2010, p.222.

component of stock returns is later investigated in the context of past-performance strategies based on annual intervals.

An example of a seasonal effect can be observed in consumption indicators of an economy. Those usually reach a peak each December due to Christmas or holiday pay.[3] Although seasonality is expected to be present in many series, there are some in which this effect is usually not observed, such as interest rates. Furthermore, many macro-economic series are already adjusted for seasonality in the source before being published, for example the quarterly U.S. GDP.[4] This study analyzes seasonal patterns on stock returns and investigates whether it should be possible to generate profits through strategies that exploit these patterns.

3 Past-Performance Based Strategies

In this section different investment strategies, based on past returns and empirical results from previous research, are presented.

3.1 Winner-Loser Strategy and Momentum

There are different settings of winner-loser strategies. One approach is based upon momentum, which consists of buying stocks which outperformed in the past (winners) and selling those that underperformed (losers). The time window for analysis of past returns is flexible. There are shorter-term strategies based on the return from the previous year, months, weeks or even days, as well as longer-term strategies where the portfolio is formed based on returns from, for example, twenty years ago.

Jegadeesh and Titman show that there are patterns in stock returns, which can be exploited by short-term trading strategies based on past-performance from the last 3-12 months, with a holding period of 3-12 months.[5] The most successful strategy is based on the last 12 months and holds the portfolio for 3 months, yielding between 1.31% and 1.49% per

[3] Cf. Winker, 2010, p.221.
[4] Cf. Wooldridge, 2012, p.371f.
[5] Cf. Jegadeesh, Titman, 1993, p.69f.

month.[6] They also give special focus to the strategy based on the last 6 months with a holding period of another 6 months, which generates higher returns especially in April, November and December.[7] The higher return is possibly due to price pressure caused by taxation law requirements, which encourage the transfer of money by corporations to pension funds before mid-April, as one of the examples.[8] These findings are consistent with a weak form of market inefficiency in the stock market, where future prices can be predicted based on historical prices.[9]

Heston and Sadka demonstrate seasonal effects which hold for the same month every year.[10] They build a variety of winner-loser strategies based on past-returns from the same month across multiple years in the past. Stocks which achieve high returns in a certain month tend to have above-average returns in yearly intervals up to 20 years.[11] This effect is attributed to seasonality in the stock returns. According to their empirical research, the decile-spread performance exceeds 50 monthly basis points. However, the transaction costs of rebalancing the whole portfolio each month, which are not incorporated into the results of the winner-loser strategies, would possibly make the strategy unprofitable.[12] In the empirical sections of this study, some of the analyses did by Heston and Sadka are explained in detail and replicated with an extended data sample.

3.2 Winner-Loser Reversals and Contrarian

There is also empirical evidence that losers outperform winners when applying a different setting of past-performance strategies, denoted as contrarian strategies, which buy past losers and sell past winners. Findings of De Bondt and Thaler show that, for a holding period of 36 months, portfolios composed by losers outperform the winners significantly by 24.6% on average.[13] They attribute this result to overreaction of the market, which is particularly pronounced in the loser portfolios.[14] To choose the winners and losers in a strategy based on the overreaction hypothesis, the extremely high and extremely low

[6] Cf. Jegadeesh, Titman, 1993, p.69f.
[7] Cf. Jegadeesh, Titman, 1993, p.80f.
[8] Cf. Jegadeesh, Titman, 1993, p.80f.
[9] Cf. Islam, Khaled, 2005, p.1615.
[10] Cf. Heston, Sadka, 2008, p.418.
[11] Cf. Heston, Sadka, 2008, p.443.
[12] Cf. Heston, Sadka, 2008, p.442f.
[13] Cf. De Bondt, Thaler, 1985, p.799.
[14] Cf. De Bondt, Thaler, 1985, p.799.

returns over periods up to five years are considered in the portfolio formation.[15] The hypothesis predicts that prices of stocks which have extreme returns tend to reverse in the long term, especially over the next two to three years.[16] These findings also reveal evidence of market inefficiency in its weak form.[17]

Furthermore, Lehmann presents strategies where loser (winner) portfolios that are formed based on past returns within the last week have positive (negative) returns in the week after. [18] However, there is little evidence for persistence of this reversal effect over the next 12 months, since returns are usually higher when the portfolios are formed based on performance from one week before, while they become lower when the considered week is located in more distant time horizons, such as 36 or 52 weeks in the past.[19]

4 Possible Explanations for Anomalies in Stock Returns

This section presents multiple factor models and behavioral theories, that potentially explain the reasons behind the high returns achieved through past-performance based strategies.

4.1 Risk Factors

It would be unreasonable to assume that past-performance is the only explanation for the returns from momentum and contrarian strategies without making some tests first. There are different additional factors that could be responsible for their performance, such as size and value.[20] Therefore, the results of the strategies are tested with the purpose of verifying if the high returns still hold after controlling them for these factors. It is also known that the Capital Asset Pricing Model (CAPM) of Sharpe and Lintner does not explain these return patterns and characterizes them as anomalies.[21] Since the high returns are not predicted by the CAPM, those are controlled for the three risk factors of the Fama-

[15] Cf. De Bondt, Thaler, 1985, p.795f.
[16] Cf. De Bondt, Thaler, 1985, p.799-801.
[17] Cf. De Bondt, Thaler, 1985, p.795.
[18] Cf. Cf. Lehmann, 1990, p.12-14.
[19] Cf. Cf. Lehmann, 1990, p.13f.
[20] Cf. Schwert, 2003, p.942-947.
[21] Cf. Fama, French, 1996, p.55.; cf. Lintner, 1965, p.13-37; cf. Sharpe, 1964, p.425-442.

French model: size in terms of capitalization, book-to-market ratio and excess of returns from a market portfolio.[22]

The reason behind the choice of these factors is that, according to empirical evidence, they explain a considerable part of the variation in the cross-section of stock returns.[23] Fama and French showed in 1996 that, the three-factor model explains the anomalies found in the mentioned contrarian strategies utilized by De Bondt and Thaler in 1985.[24] However, it fails to explain the presented short-term momentum effect observed by Jegadeesh and Titman in 1993.[25] Similarly, Heston and Sadka present evidence that the high returns from strategies based on past performance in the same calendar month of previous years are also not explained by the three-factor model.[26] This test is also implemented in the empirical part of this study, with an extended data sample.

4.2 Behavioral Models

Since the momentum anomaly is apparently not explained by risk factors, there might be other explanations for it, such as market underreaction and behavioral models.[27] The market underreaction hypothesis assumes that investors tend to rank received information according to the time when it arises, so that new information is less important than old information, and hence has a lower weight in the portfolio formation.[28] Moreover, behavioral models seem able to partially explain the momentum anomaly.[29] Therefore, some of them are explained next.

One behavioral model that is consistent with the mentioned abnormal patterns in stock returns is the theory of Daniel et al. based on overconfidence and self-attribution bias, which says that investors are overconfident about their own judgements, underestimate public information signals and, at the same time, underestimate their own forecasting errors. [30] Due to this overconfidence, gains are predominantly attributed by the investor to his or her own capacities, causing the price to overreact to individual investor signals,

[22] Cf. Fama, French, 1996, p.55f.
[23] Cf. Fama, French, 1996, p.55f.
[24] Cf. Fama, French, 1996, p.63-68.
[25] Cf. Fama, French, 1996, p.81f.
[26] Cf. Heston, Sadka, 2008, p.425f.
[27] Cf. Jegadeesh, Titman, 2001, p.708f.
[28] Cf. Jegadeesh, Titman, 2001, p.708-710.
[29] Cf. Jegadeesh, Titman, 2001, p.719.
[30] Cf. Daniel, Hirshleifer, Subrahmanyam, 1998, p.1841.

but underreact to market information.[31] If public information is found to confirm the investor's position, the investor's confidence is boosted, and contributes to the short-term autocorrelation in the stock returns, resulting in momentum opportunities.[32] Conversely, when the public signal disconfirms the investor's trade, the investor's confidence decreases by little and prices converge only gradually into their fundamentals, causing a long-term reversal in the stock returns.[33]

Hong and Stein proposes a model which divides the market into two groups of rational investors, denoted by newswatchers and momentum traders, where both are bounded in the sense that they are only able to process one part of the publicly available information: the newswatchers consider fundamental information for their investment decisions but ignore prices, while momentum traders consider only prices and ignore fundamentals.[34] This model shows that newswatcher underreact to the fundamentals, creating a trend seen as an opportunity for the momentum traders, who trade based on the price changes caused by previous trades.[35] Consequently, prices converge gradually through time to their fundamental value, which is eventually exceeded due to the overreaction of momentum traders that build their position too late.[36] This is also consistent with short-term momentum and long-term reversal.

An additional model from Barberis et al., based on conservatism and representativeness heuristic, assumes that investors choose between two models, according to which regime is currently valid: model 1 is applied when investors believe that earnings follow a mean-reverting process and model 2 is used when a trend is identified.[37] Since none of them are in accordance with the random walk process assumed by the model, the existence of under- and overreaction becomes possible under this framework.[38]

Finally, although the presented alternative explanations show evidence that are consistent with momentum and contrarian anomalies, it is important to identify which strategies they are consistent with. Heston and Sadka argue that, in order to be consistent with the high returns resulting from the seasonal strategies presented by them, behavioral models must be able to explain the abrupt changes in the expected returns from one month to adjacent

[31] Cf. Daniel, Hirshleifer, Subrahmanyam, 1998, p.1841.
[32] Cf. Daniel, Hirshleifer, Subrahmanyam, 1998, p.1855f.
[33] Cf. Daniel, Hirshleifer, Subrahmanyam, 1998, p.1855f.
[34] Cf., Hong, Stein, 1999, p.2144f.
[35] Cf., Hong, Stein, 1999, p.2145.
[36] Cf., Hong, Stein, 1999, p.2145f.
[37] Cf., Barberis, Schleifer, Vishny, 1998, p.318f.
[38] Cf., Barberis, Schleifer, Vishny, 1998, p. 318-320.

months, and the seasonality in the stock returns.[39] For instance, returns from strategies based on performance from 12 months in the past may differ on average in more than 140 basis points from strategies based on historical returns from 13 or 14 months before.[40]

4.3 Mispricing Factors

The four-factor model of Stambaugh and Yuan indicates evidence that a model composed by two risk factors (size and market's excess return), together with two additional mispricing factors, should explain momentum anomalies.[41] Notably, the book-to-market factor from Fama and French is not included. The reason for this is that it is already priced by the mispricing factors.[42] Besides, this model combines frequent and Bayesian approaches in a way that investor sentiment predicts the mispricing factors.[43]

Furthermore, the mispricing factors, denoted by MGMT and PERF, are constructed based on 11 anomalies, which are divided in two clusters according to their similarity.[44] MGMT contains anomalies that the management should be able to affect directly, which are accruals, net operating assets, asset growth, investment to assets, composite equity issues and new stock issues, while PERF is composed by the performance-related anomalies momentum, distress, O-score, gross profitability and return on assets.[45] What distinguishes this model from others that also document anomalies, is the fact that each of the two mispricing factors is calculated based on multiple anomalies, instead of a single one.[46]

Since the four-factor model including mispricing factors shows evidence to explain anomalies in stock returns better than other multiple-factor models, such as the mentioned three-factor model and the five-factor model of Fama and French, it is also implemented in the empirical work of this study.[47]

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[39] Cf. Heston, Sadka, 2008, p.443.
[40] Cf. Heston, Sadka, 2008, p.443
[41] Cf. Stambaugh, Yuan, 2017, p.1270f.
[42] Cf. Stambaugh, Yuan, 2017, p.1275.
[43] Cf. Stambaugh, Yuan, 2017, p.1272.
[44] Cf. Stambaugh, Yuan, 2017, p.1276-1278.
[45] Cf. Stambaugh, Yuan, 2017, p.1276-1278.
[46] Cf. Stambaugh, Yuan, 2017, p.1285.
[47] Cf. Fama, French, 1993, p.19-26; cf. Fama, French, 2015, p.2f; cf. Stambaugh, Yuan, 2017, p.1286-1292.

5 Empirical Analysis

With the purpose of investigating the seasonal momentum effect in stock returns, the empirical part of this study replicates, with an extended data sample, the cross-sectional simple regressions and the winner-loser strategies applied by Heston and Sadka in 2008.[48] Furthermore, delisting returns are incorporated and the obtained results are controlled for mispricing factors in addition to risk factors.

5.1 Extended Data Sample

The data sample used for the subsequent empirical analyses consists of monthly stock returns from firms listed on the stock exchanges NYSE and AMEX, for the period from January 1945 until December 2016. The data source is the Center for Research in Security Prices (CRSP). This sample is chosen in order to identify whether the results found by Heston and Sadka in 2008 still hold after extending the covered period, which was originally from January 1965 until December 2002 in their research.[49] Returns from 1945 are necessary for past-performance based strategies applied in 1965 which depend on up to 20 years of historical data.

To illustrate how the data obtained from CRSP in a monthly basis looks like, Table 1 contains a sample of the data as an example. After filtering the data by firms traded on NYSE and AMEX only, there are over two million available monthly returns. These are represented by the headers RET and DLRET, which stand for monthly return and delisting return, respectively. Firms are identified by the variable PERMNO, which is a sort of unique ID given for each traded company. The exchange where the stock is listed is identified by the field EXCHCD, which stands for exchange code. This field is necessary to filter AMEX and NYSE listed stocks. For this purpose, only companies with the following EXCHCD were selected: 1, 31, 2 and 32. The first two stand for NYSE companies, while the other two represent AMEX.[50] The field SHRENDDT, which stands for shares observation end date, is used to identify the delisting date, since according to

[48] Cf. Heston, Sadka, 2008, p.418-426.
[49] Cf. Heston, Sadka, 2008, p.418-426.
[50] Cf. Bali, Engle, Murray, 2016, p.105.

the data definitions from CRSP, "the SHRENDDT of the last observation is set to be the delisting date".[51]

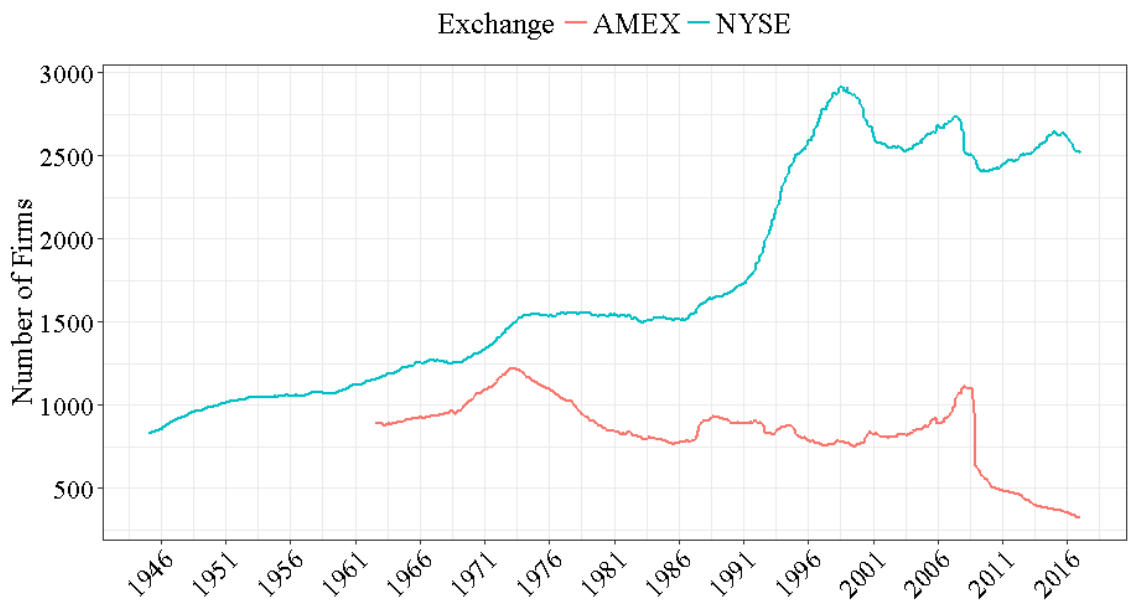
Table 1. Example of extended data sample.

PERMNO	date	RET	EXCHCD	SHRENDDT	DLRET
89951	20130731	0.013063	2	20130829	
89951	20130830	0.320587	2	20130929	
89951	20130930	-0.215488	2	20131030	
89951	20131031	-0.227468	2	20131031	-0.044444

Source data: CRSP

Since the empirical analysis executes past-performance strategies that require monthly returns up to 20 years ago, there must be enough firms with such large historical data, so that the results are reliable. Therefore, the number of firms by each year is plotted in Figure 1, which indicates large numbers of observations within the whole period.

Figure 1. Number of firms by year.

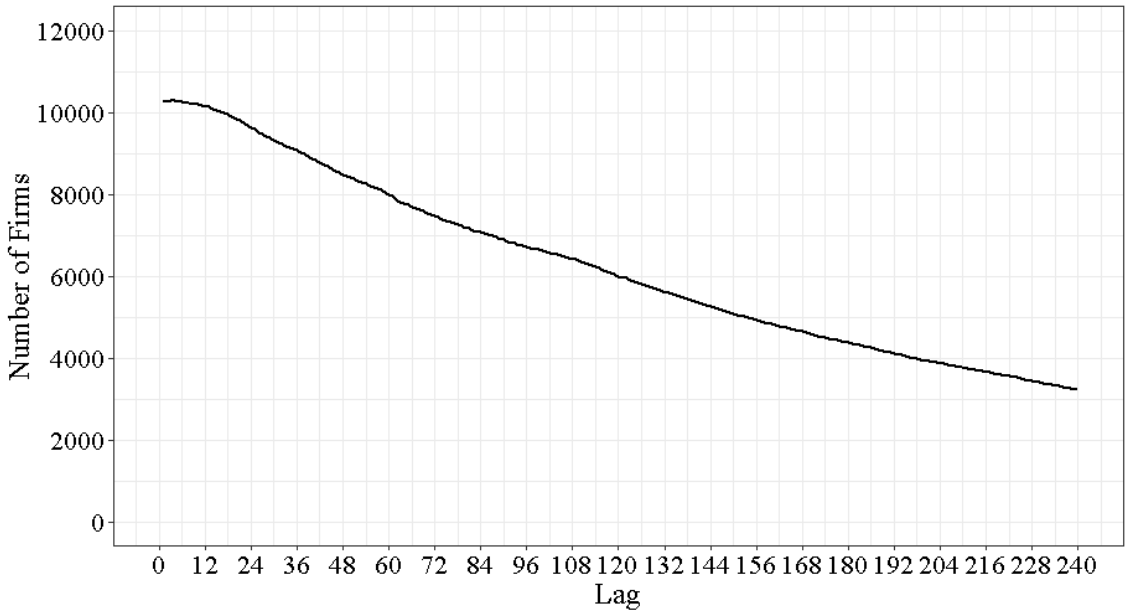


Source data: CRSP

Another important point is the availability of past-performance information. If a strategy is based on returns from 15 to 20 years ago, there is a concern about the number of firms that have this information.[52] Therefore, Figure 2 indicates how many firms have available information in the past *k* months. As expected, the number of firms decreases by increasing lag.

[51] CRSP, 2017, p.80.
[52] Cf. Heston, Sadka, 2008, p.420.

Figure 2. Number of available firms by lag.



Source data: CRSP

However, there is still a considerable number of firms which have past-performance data up to 20 years ago. More than 2500 firms contain monthly returns for at least 240 consecutive months. This contributes to the accuracy of the results from past-performance based strategies presented in the following sections.

5.2 Cross-Sectional Regression of Monthly Returns

Heston and Sadka apply the cross-sectional regression methodology from Fama and MacBeth to monthly stock returns, to verify if the effects of past returns from the same calendar month on the current returns are larger than the effects of past returns from adjacent months.[53] The applied simple cross-sectional regression of monthly return is expressed in equation 1.

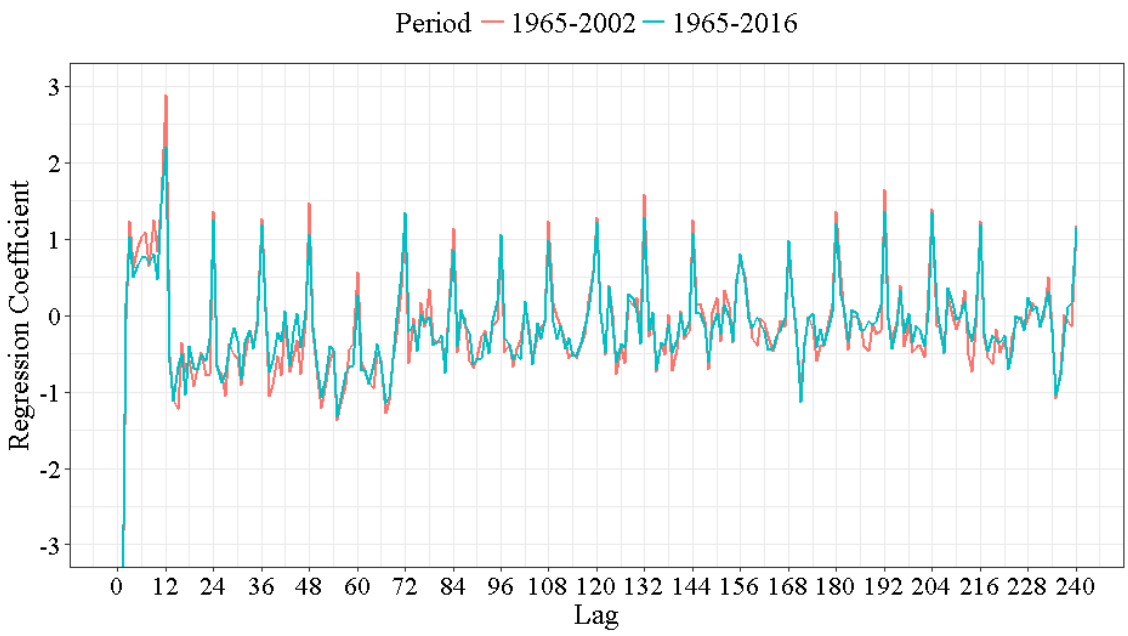
(1)[54] $$\hat{r}_{i,t} = \hat{\alpha}_{k,t} + \hat{\gamma}_{k,t} r_{i,t-k}$$

This regression is calculated for each month *t* between January 1965 and December 2016, and each lag *k* from 1 to 240. The estimated monthly return of stock *i* in month *t* is denoted by $\hat{r}_{i,t}$. Moreover, $r_{i,t-k}$ is the monthly return of the stock *i* in month *t* – *k*, $\hat{\alpha}_{k,t}$ is the

[53] Cf. Fama, French, 1992, p.438-44; cf. Fama, MacBeth, 1973, p.614-624; cf. Heston, Sadka, 2008, p.421f.
[54] Cf. Heston, Sadka, 2008, p.421f.

intercept and $\hat{\gamma}_{k,t}$ is the coefficient, which represents the effect of the lagged return on the current return.[55] After calculating the month-by-month regression coefficients estimates, denoted by $\hat{\gamma}_{k,t}$, the average for each lag, $\bar{\hat{\gamma}}_k$, is calculated.[56] Figure 3 plots $\bar{\hat{\gamma}}_k$ for each lag, in percent, and compare the coefficients obtained for the extended period (January 1965 - December 2016) with those calculated for the shorter period originally covered by Heston and Sadka in 2008 (January 1965- December 2002).[57]

Figure 3. Average simple regression estimates including extended period.



Source data: CRSP

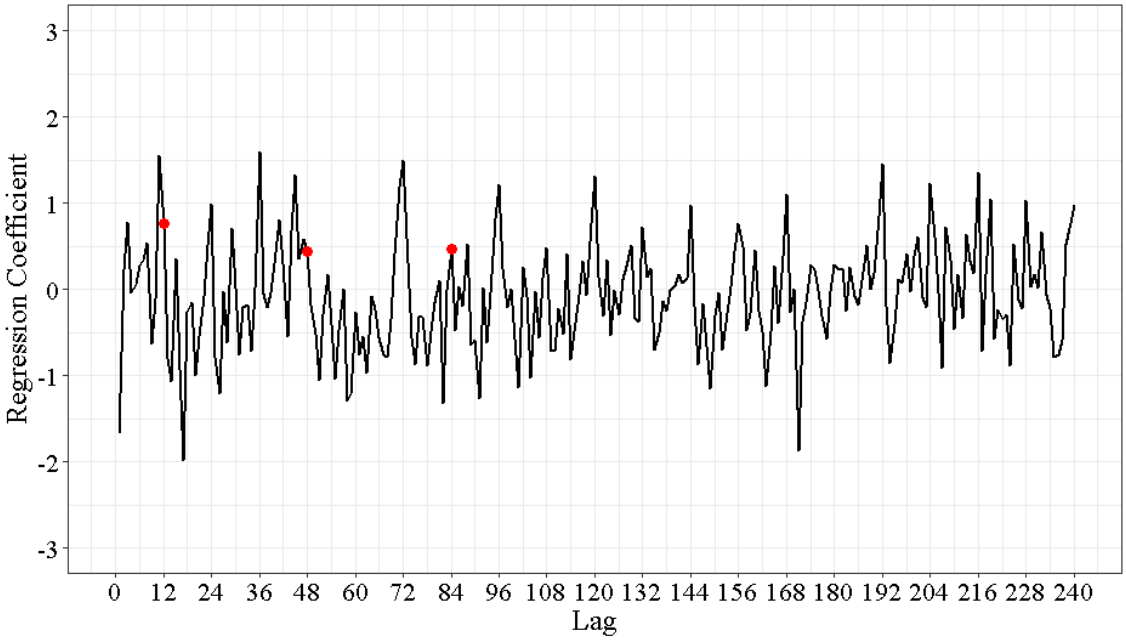
Figure 3 shows that the coefficients from lags that are multiples of 12 are mostly larger for the period 1965-2002, represented by the red line, than for 1965-2016, represented by the blue line. This effect can be graphically observed through the red peaks, that are predominantly higher than the blue ones. Furthermore, coefficients for the out-of-sample period from January 2003 to December 2016 are also mostly smaller. Therefore, there is evidence that the seasonal effect found by Heston and Sadka in 2008 becomes weaker in more recent years. This justifies a further investigation of the coefficients for shorter periods to identify when the seasonal momentum effect is particularly stronger or weaker. The exact average coefficient values and their respective t-statistics for the three periods mentioned above, for lags from 1 to 12 and multiples of 12 from 24 to 240, are reported in Table 7 in the appendix. All the t-statistics of this study, including the reported Fama

[55] Cf. Heston, Sadka, 2008, p.422.
[56] Cf. Fama, MacBeth, 1973, p.619.; cf. Heston, Sadka, 2008, p.421f.
[57] Cf. Heston, Sadka, 2008, p.422.

and MacBeth t-statistics, are adjusted for heteroskedasticity and autocorrelation using the correction from Newey and West with up to 12 lags.[58] This is the same approach adopted by Heston and Sadka in 2008.[59]

In order to proceed with the further investigation by shorter periods, the dataset is divided into three periods: 2000-2016, 1983-1999 and 1965-1982. The same method is then applied to calculate the cross-sectional regressions of monthly stock returns within these three periods separately. Interestingly, Figure 4, which contains the results for the most recent period 2000-2016, illustrates how the effect of lagged returns for lags that are multiple of 12 decreases, especially for the lags 12, 48 and 84, which are marked in red.

Figure 4. Average simple regression estimates for the period 2000-2016.



Source data: CRSP

The effect of the marked lags is even lower than the effect of adjacent lags that are not multiples of 12. For instance, the coefficients of lags 11, 47 and 88 are higher than the coefficients of lags 12, 48 and 84 respectively. A possible explanation for the first two cases could be a greater activity of front-running trades, which anticipates the yearly seasonal effect and pick, for example, the stocks with the best returns 11 months ago, knowing that these stocks will be bought in the next month by the investors following the yearly strategy. Previous empirical research shows that front-running a momentum strategy delivers generally similar, but less volatile returns than the usual month-end

[58] Cf. Fama, MacBeth, 1973, p.619; cf. Newey, West, 1987, p.703-707.
[59] Cf. Heston, Sadka, 2008, p.423.

strategy, where the investors set their portfolio in the end of each month.[60] The lower volatility can be an incentive for investors to front-run momentum strategies.

Since the findings in Figure 4 indicate that the yearly seasonal effects tend to fade for more recent periods, the average coefficients and t-statistics for the three shorter periods are compared in Table 2, which shows evidence that the yearly seasonal effects for the lags 12, 24, and 48 in 2000-2016, apart from becoming weaker in comparison to the previous period, also lose statistical significance at the 0.05 level.

Table 2. Simple cross-sectional regressions of returns for different periods.

	1965-1982		1983-1999		2000-2016	
Lag	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
1	-6.95	-6.79	-4.26	-7.08	-1.68	-3.34
2	0.41	0.57	-0.20	-0.42	0.22	0.28
3	1.40	2.25	0.89	1.77	0.78	1.21
4	1.67	2.38	-0.18	-0.47	-0.04	-0.07
5	0.78	1.08	1.13	2.22	0.06	0.09
6	0.80	1.23	1.20	2.08	0.26	0.26
7	0.67	1.20	1.34	3.62	0.34	0.45
8	0.55	0.79	0.97	1.62	0.53	0.91
9	1.30	1.90	1.71	3.66	-0.64	-0.94
10	0.59	1.09	0.93	2.18	-0.11	-0.13
11	1.74	3.68	1.04	1.74	1.55	1.83
12	3.08	5.55	2.73	5.74	0.76	1.43
24	0.44	0.75	2.39	6.95	0.99	1.75
36	0.77	1.44	1.20	2.73	1.59	2.18
48	0.85	1.26	1.89	3.52	0.44	0.70
60	0.42	0.59	0.63	1.46	-0.26	-0.39
72	1.62	3.22	0.89	1.76	1.49	2.93
84	1.33	2.64	0.76	1.72	0.47	1.11
96	0.97	1.19	1.03	2.34	1.21	3.05
108	1.28	1.95	1.17	2.57	0.47	1.24
120	1.47	3.10	0.85	2.04	1.31	2.64
132	1.75	3.36	1.34	3.38	0.71	1.26
144	0.85	1.45	1.40	3.18	0.98	2.76
156	0.98	1.58	0.65	1.47	0.76	1.17
168	1.01	1.29	0.85	2.37	1.11	2.10
180	1.39	2.57	1.91	3.52	0.28	0.65
192	0.45	0.73	2.26	4.08	1.45	1.93
204	1.41	2.06	1.40	3.54	1.23	2.51
216	1.63	2.19	0.55	1.24	1.36	2.77
228	-0.38	-0.48	0.06	0.13	1.03	2.13
240	1.49	2.46	0.95	1.83	0.97	2.18

Source data: CRSP

[60] Cf. Henker, Martens, Huynh, 2006, p.3.

However, this does not apply for longer lags. For the period 2000-2016, all average coefficients for the yearly lags from 204 to 240 are statistically significant. This is not seen in the other two previous periods where, for example, the average coefficient for lag 228 is not significant. Another interesting point is that the reversal effect observed in lag 1 remains significant in all periods. Nevertheless, this effect weakens over time, as the coefficient changes from -6.95 in 1965-1982 to -1.68 in 2000-2016.

Furthermore, in order to verify whether the observed yearly seasonal effects are still capable to generate returns after extending the data sample, winner-loser strategies with different setups will be analyzed in the next section.

5.3 Winner-Loser Strategies

Winner-loser strategies are applied such that each month ten portfolios are built based on the past performance of the stocks. Portfolio deciles are built, such that portfolio number 1 contains the worst 10% of stocks in terms of average past returns and portfolio 10 contains the top 10%. The same weight is given for all stocks in each portfolio. The same strategies applied by Heston and Sadka in 2008 are applied, but for three different periods (1965-1982, 1983-1999 and 2000-2016) and with an extended data sample.[61] The objective of this division in three distinct periods is to investigate when those strategies generate returns or not, and whether the returns decrease through time.

Three different strategies, based on returns from five distinct time intervals in the past, are applied. The strategies are called all, annual and non-annual, while the time intervals observed in the past are: year 1, years 2-5, years 6-10, years 11-15 and years 16-20.[62] The strategy all determines the portfolios based on the average of all monthly returns within the corresponding time interval. The strategy annual is based only on the lagged returns within the interval whose lags are multiples of 12, i.e. past returns from the same calendar month. The strategy non-annual considers only the lags which are not multiples of 12. As an example, consider the time interval years 2-5. In this case, the all-months strategy is based on the average of all lagged returns within the lags 13 to 60. The annual strategy considers only the lags 24, 36, 48 and 60. Finally, the strategy non-annual takes into

[61] Cf. Heston, Sadka, 2008, p.425.
[62] Cf. Heston, Sadka, 2008, p.424f.

account all lags from the strategy based on all months except those from the annual strategy.[63] Table 3 shows the average monthly returns of portfolios 1 and 10 in percent, and the average difference between those two portfolios after applying the mentioned winner-loser strategies, as well as the t-statistics (in brackets). The difference 10-1 is also characterized as decile spread portfolio, which buys portfolio 10 (winners) and sells portfolio 1 (losers).

Table 3. Winner-loser strategies.

Period	1965-1982			1983-1999			2000-2016		
Portfolio	1	10	10-1	1	10	10-1	1	10	10-1
Year 1									
All	1.37	1.86	0.49	0.76	1.64	0.88	1.10	1.29	0.19
	[2.22]	[3.31]	[1.25]	[1.75]	[4.42]	[2.89]	[1.34]	[2.67]	[0.29]
Annual	0.87	2.16	1.29	0.35	1.67	1.32	0.97	1.28	0.31
	[1.48]	[3.53]	[5.32]	[1.06]	[4.49]	[7.09]	[1.67]	[2.64]	[1.24]
Non Annual	1.58	1.70	0.12	1.03	1.56	0.53	1.13	1.29	0.16
	[2.47]	[3.07]	[0.26]	[2.23]	[4.43]	[1.58]	[1.37]	[2.67]	[0.23]
Years 2-5									
All	2.06	0.65	-1.41	1.58	0.96	-0.62	1.48	0.88	-0.61
	[4.06]	[1.15]	[-5.11]	[3.21]	[2.92]	[-1.42]	[2.26]	[1.81]	[-1.41]
Annual	1.16	1.71	0.55	0.60	1.79	1.19	0.86	1.33	0.47
	[2.13]	[3.08]	[2.02]	[1.65]	[5.55]	[6.44]	[1.71]	[2.79]	[1.71]
Non Annual	2.23	0.55	-1.68	1.75	0.79	-0.96	1.55	0.76	-0.79
	[4.28]	[0.97]	[-6.08]	[3.68]	[2.40]	[-2.38]	[2.31]	[1.56]	[-1.77]
Years 6-10									
All	1.40	1.26	-0.14	1.30	0.94	-0.36	1.40	0.83	-0.57
	[2.89]	[2.52]	[-0.63]	[3.90]	[2.89]	[-1.62]	[3.15]	[1.74]	[-3.13]
Annual	0.97	1.82	0.85	0.83	1.61	0.78	0.82	1.51	0.69
	[1.94]	[4.18]	[5.42]	[2.91]	[4.67]	[4.27]	[1.89]	[3.30]	[3.74]
Non Annual	1.58	1.16	-0.42	1.46	0.89	-0.57	1.59	0.75	-0.85
	[3.27]	[2.26]	[-1.89]	[4.27]	[2.77]	[-2.31]	[3.72]	[1.61]	[-5.28]
Years 11-15									
All	1.08	1.30	0.22	1.32	1.35	0.02	1.40	1.00	-0.39
	[2.61]	[2.96]	[0.93]	[4.08]	[4.51]	[0.14]	[3.23]	[2.35]	[-2.11]
Annual	0.83	1.77	0.95	0.83	1.67	0.84	0.80	1.41	0.61
	[1.99]	[4.08]	[5.58]	[2.64]	[5.80]	[6.40]	[1.81]	[3.31]	[3.53]
Non Annual	1.28	1.32	0.03	1.53	1.18	-0.35	1.55	0.91	-0.64
	[3.26]	[2.99]	[0.15]	[4.79]	[3.80]	[-1.66]	[3.61]	[2.14]	[-3.21]
Years 16-20									
All	1.43	0.94	-0.49	1.23	1.36	0.13	1.12	1.16	0.04
	[3.42]	[2.47]	[-2.41]	[4.07]	[5.02]	[0.58]	[2.65]	[2.63]	[0.26]
Annual	0.89	1.38	0.49	0.81	1.61	0.80	0.69	1.50	0.80
	[2.16]	[3.57]	[2.82]	[2.79]	[5.48]	[4.26]	[1.50]	[3.86]	[4.32]
Non Annual	1.49	0.93	-0.55	1.36	1.12	-0.23	1.32	1.03	-0.29
	[3.54]	[2.53]	[-3.00]	[4.08]	[3.96]	[-0.85]	[3.26]	[2.37]	[-1.72]

Source data: CRSP

[63] Cf. Heston, Sadka, 2008, p.424f.

Table 3 shows that, for the period 2000-2016, the decile spread for the annual strategy lost its significance for year 1, where the decile spread is only 31 basis point and the t-statistic 1.24. It is a large decrease compared to the statistically significant decile spreads of 129 and 132 basis points in the two previous periods. Besides, the decile spread of the annual strategy for years 2-5 in 2000-2016 also lost its significance at the 0.05 level. However, for the more distant yearly intervals 6-10 and 11-15, the decile spread returns on annual strategies in 2000-2016 are still significant and the decreases are not so large as for year 1. Moreover, for the interval 16-20, the annual decile spread performance in 2000-2016 does not change in comparison to the previous period and remains statistically significant. Therefore, despite the decrease and loss of statistical significance in the annual decile spreads for shorter-term intervals (year 1 and years 2-5), the winner portfolio based on the annual strategy still outperforms the loser portfolio significantly in 2000-2016 for longer-term yearly intervals (years 6-10, 11-15 and 16-20).

Since the analysis above is based solely on the monthly returns provided by CRSP under the field RET, there is a concern that the results may be in some extent biased by the omission of delisting returns. Hence, these are incorporated into the analysis in the next section.

5.4 Winner-Loser Strategies Including Delisting Returns

Delisting return, as defined in the CRSP data descriptions guide, is "the return of a security after it is delisted".[64] Sometimes, delisting events are unpredictable and investors do not have the chance to sell the stock before it happens.[65] This should affect the performance of the applied investment strategies.

There is empirical evidence that the inclusion of delisting returns modifies the return of trading strategies based on fundamental variables such as book-to-market ratio, cash flows, earnings and accruals because of the disproportional number of delisted firms in the lowest decile.[66] This raises a concern that omitted delisting returns may also have an impact on the average returns of the winner-loser strategies presented in this work. To

[64] CRSP, 2017, p.95.
[65] Shumway, 1997, p.327.
[66] Cf. Beaver, McNichols, Price, 2007, p.358-364.

investigate these possible impacts, the delisting returns, also obtained from CRSP, are incorporated into the monthly returns.

The calculation behind the monthly delisting returns defined by CRSP, denoted by DLRET in the data sample, differs when the delisting occurs before the last trading day of the month and when it happens on the last trading day.[67] If the delisting occurs before the last trading day, the provided month delisting return includes the delisting return and the partial monthly return of the delisting month until the delisting, while when the delisting occurs on the last trading day of the month, the provided monthly delisting return includes only the delisting return.[68] This calculation is given by equation 2, where $mdr_{i,d}$ represents the monthly delisting return of stock i in the delisting month, $dr_{i,d}$ is the delisting return, d is the delisting date, ltd stands for last trading day of the month and $r_{i,d}$, represents monthly stock return in the delisting month, which is characterized as a partial month return when $d < ltd$, since in this case it covers only the period from the begin of the month until the delisting event. [69]

(2)[70]
$$mdr_{i,d} = \begin{cases} (1 + dr_{i,d})(1 + r_{i,d}) - 1 & \text{if} \quad d < ltd \\ dr_{i,d} & \text{if} \quad d = ltd \end{cases}$$

According to this schema, the adjusted monthly return of the delisting month is calculated as described in equation 3. $r^*{}_{i,d}$ represents the calculated adjusted monthly return of the delisting month, $r_{i,d}$ is the monthly stock return in the delisting month and $mdr_{i,d}$ is the monthly delisting return, which already includes the partial month return when the delisting occurs before the last trading day of the month.

(3)
$$r^*{}_{i,d} = \begin{cases} mdr_{i,d} & \text{if} \quad d < ltd \\ (1 + mdr_{i,d})(1 + r_{i,d}) - 1 & \text{if} \quad d = ltd \end{cases}$$

Another issue which may lead to biased results are the missing values for some delisting returns in the database from CRSP. In the cases where delisting returns are omitted, a proxy of -30% is used based on empirical evidence that this should be the average

[67] Cf. Beaver, McNichols, Price, 2007, p.366.
[68] Cf. Beaver, McNichols, Price, 2007, p.366.
[69] Cf. Beaver, McNichols, Price, 2007, p.366.
[70] Cf. Beaver, McNichols, Price, 2007, p.366.

delisting return for the missing values.[71] Table 4 contains the results of the winner-loser strategies after considering the delisting returns.

Table 4. Winner-loser strategies incl. delisting returns.

Period	1965-1982			1983-1999			2000-2016		
Portfolio	1	10	10-1	1	10	10-1	1	10	10-1
Year 1									
All	1.27	1.84	0.57	0.49	1.61	1.12	0.66	1.24	0.58
	[2.06]	[3.32]	[1.48]	[1.14]	[4.44]	[3.65]	[0.80]	[2.61]	[0.89]
Annual	0.82	2.13	1.31	0.17	1.61	1.44	0.74	1.19	0.45
	[1.39]	[3.48]	[5.32]	[0.51]	[4.34]	[6.93]	[1.26]	[2.45]	[1.79]
Non Annual	1.49	1.70	0.21	0.75	1.53	0.78	0.69	1.24	0.55
	[2.32]	[3.09]	[0.45]	[1.65]	[4.45]	[2.33]	[0.84]	[2.62]	[0.79]
Years 2-5									
All	2.01	0.63	-1.38	1.34	0.93	-0.40	1.19	0.84	-0.34
	[3.91]	[1.11]	[-5.00]	[2.87]	[2.84]	[-0.99]	[1.81]	[1.74]	[-0.82]
Annual	1.12	1.66	0.53	0.48	1.73	1.24	0.71	1.25	0.53
	[2.05]	[2.95]	[1.95]	[1.35]	[5.38]	[6.69]	[1.40]	[2.63]	[1.89]
Non Annual	2.17	0.53	-1.65	1.50	0.76	-0.74	1.27	0.72	-0.55
	[4.15]	[0.93]	[-6.01]	[3.30]	[2.32]	[-1.94]	[1.91]	[1.48]	[-1.28]
Years 6-10									
All	1.40	1.25	-0.14	1.17	0.90	-0.28	1.30	0.77	-0.53
	[2.88]	[2.50]	[-0.63]	[3.48]	[2.77]	[-1.18]	[2.94]	[1.60]	[-2.85]
Annual	0.95	1.80	0.85	0.76	1.55	0.80	0.73	1.44	0.71
	[1.90]	[4.13]	[5.45]	[2.61]	[4.59]	[4.31]	[1.66]	[3.18]	[3.71]
Non Annual	1.58	1.17	-0.41	1.34	0.86	-0.48	1.50	0.68	-0.82
	[3.27]	[2.25]	[-1.87]	[3.89]	[2.68]	[-1.87]	[3.53]	[1.47]	[-4.99]
Years 11-15									
All	1.08	1.29	0.21	1.26	1.30	0.04	1.35	0.93	-0.42
	[2.62]	[2.94]	[0.89]	[3.90]	[4.43]	[0.20]	[3.10]	[2.18]	[-2.37]
Annual	0.82	1.78	0.95	0.78	1.65	0.87	0.75	1.35	0.59
	[1.99]	[4.08]	[5.59]	[2.48]	[5.82]	[6.52]	[1.71]	[3.17]	[3.59]
Non Annual	1.31	1.31	0.01	1.47	1.13	-0.34	1.49	0.83	-0.66
	[3.31]	[2.99]	[0.03]	[4.61]	[3.65]	[-1.63]	[3.45]	[1.95]	[-3.32]
Years 16-20									
All	1.43	0.94	-0.48	1.21	1.32	0.11	1.08	1.09	0.01
	[3.41]	[2.46]	[-2.34]	[4.11]	[4.89]	[0.53]	[2.57]	[2.47]	[0.06]
Annual	0.90	1.39	0.49	0.77	1.59	0.82	0.63	1.42	0.79
	[2.17]	[3.59]	[2.73]	[2.65]	[5.42]	[4.08]	[1.36]	[3.70]	[4.27]
Non Annual	1.48	0.92	-0.56	1.34	1.09	-0.26	1.28	0.96	-0.32
	[3.52]	[2.51]	[-2.92]	[4.17]	[3.86]	[-0.95]	[3.16]	[2.21]	[-1.87]

Source data: CRSP

Table 4 shows that the shorter-term intervals (year 1 and years 2-5), in more recent times (2000-2016), are more affected by the delisting returns than the longer-term intervals (years 6-10, years 11-15 and years 16-20) in older periods. The largest statistically significant change within the decile spreads is the increase of 0.25% (from 0.53% to 0.78%) in the non-annual strategy for the year 1 and period 1983-1999, where the decile

[71] Cf. Shumway, 1997, p.340

spread becomes significant only after including the delisting returns. The largest decile spread increases are predominantly found within the period 2000-2016, followed by 1983-1999 and 1965-1982. This represents an evidence that the effects of the delisting returns on winner-loser strategies have been increasing constantly over the last decades. These findings can be well visualized in Table 8 in the appendix, which contains a heatmap highlighting the largest differences between the average returns from Table 4 and from Table 3.

Regarding the shorter-term intervals (year 1 and years 2-5), there is an increase in the decile spread return for all three strategies (all, annual and non-annual) within all three periods (1965-1982, 1983-1999 and 2000-2016), except for the annual strategy for years 2-5 and period 1965-1982. This increase is consistent with the hypothesis that the lowest decile portfolios are negatively affected by the inclusion of delisting returns due to the poor performance of their delisted firms. In fact, the average performance of portfolio 1 in the short-term intervals (years 1 and years 2-5) decreases for all strategies and periods. However, it is important to notice that not all decile spread returns are statistically significant. For the period 2000-2016, despite of the increase in their performance, the decile spread returns are still not significant at the 0.05 level for annual strategies based on year 1 and years 2-5.

With respect to the longer-term intervals (years 6-10, 11-15 and 16-20), the decile spreads do not change much after including delisting returns. The longer the interval, the lower the difference between the decile spreads. The decile spread from the annual strategy does not change more than 3 basis points for any of the three periods. The largest change is for the period 1983-1999, where the decile spread return from the annual strategy based on years 11-15 increases from 0.84% to 0.87%. Possibly, delisted firms tend to be traded for shorter periods before being delisted. If we assume that a firm which is traded for many years is still listed because it is characterized as a stable firm, there should not be many reasons for delisting it.

Moreover, in order to investigate the maximum magnitude of the bias caused by missing delisting returns, the proxy of -30% for the missing values is replaced with -100% in another test.[72] Assuming that the delisted stocks with missing delisting returns are mostly within the losers' portfolio, it is reasonable to think that the return of the lowest decile portfolio should decrease and the return of the decile spread increase. The fact that the

[72] Cf. Shumway, 1997, p.337.

portfolios are equally-weighted should also enlarge the effects.[73] However, the effect of substituting the proxy of -30% by -100% in the analysis is marginal and can almost not be seen. The average monthly returns on the annual strategies based on year 1 and years 2-5 remain insignificant. The t-statistic for year 1 increases only by 0.01, to 1.80, while the t-statistic for the years 2-5 does not change at all and remains 1.89. The complete results can be seen in Table 9 in the appendix. A reasonable explanation for this limited effect is the decrease in the number of omitted delisting returns in the CRSP database. In 1993, only about 72.1% of the delisted firms from NYSE and AMEX had stored delisted returns.[74] In the extended data sample obtained for this study, there are only 36 omitted values from a total of 8617 delisted returns. Hence, CRSP has apparently treated this issue in its database over the last years.

Furthermore, there may be other factors that explain the significant decile spreads other than the past returns and delisting returns. There could be a reasonable explanation based on risk, which is discussed next. [75]

5.5 Risk-adjusted Returns

In order to investigate whether there is a risk-based explanation for the high returns achieved by the winner-loser strategies, the three factors of Fama and French are incorporated into the analysis.[76] The three factors consist of SMB (small minus big), HML (high minus low) and RM-RF. SMB aims to capture the risk factor related to size in terms of market capitalization, HML is related to book-to-market ratio and RM-RF refers to excess of risk free rate. The monthly factors are available online in the Kenneth R. French data library, indicated in section VII.

To incorporate the three risk factors into the analysis, the monthly returns (excess of risk free rate) from the decile portfolios including delisting returns, which are used as basis for the analysis in Table 4 in the previous section, are regressed on the three factors RM-RF, SMB and HML. The intercepts of these time-series regressions are the risk-adjusted returns, which are reported in Table 5, in percent.[77] The regressions are calculated for

[73] Cf. Shumway, 1997, p.336f.
[74] Cf. Shumway, 1997, p.329
[75] Cf. Heston, Sadka, 2008, p.425.
[76] Cf. Fama, French, 1993, p.9f
[77] Cf. Fama, French, 1993, p.9f; cf. Heston, Sadka, 2008, p.425f.

each portfolio, strategy and period separately, according to equation 4, where PR_{jt} is the monthly return of portfolio *j* in month *t* and the intercept and a_j is the risk-adjusted return of portfolio j. Moreover, the regression coefficients β_j, s_j, and h_j measure the exposure to market, size and value risk respectively.[78]

(4)[79] $$PR_{jt} - RF_t = a_j + \beta_j(RM_t - RF_t) + s_j SMB_t + h_j HML_t + e_{jt}$$

Fama and French show that stocks with a high (low) book value in comparison to its price should achieve persistent low (high) earnings on assets, whereas smaller firms in terms of market capitalization tend to have lower earnings than larger firms.[80] If the decile-spread portfolios are exposed to these factors, it is expected that they are composed by the riskiest stocks, and that the high returns may be explained by the risk factors, instead of the seasonality in stock returns.[81]

Table 5 indicates that, for the longer-term intervals (years 6-10, years 11-15 and years 16-20), the decile spreads still have the same magnitude. This is consistent with the results found by Heston and Sadka who show, with a shorter data sample, that annual strategies based on month-performance from up to 20 years ago deliver risk-adjusted high returns, whereas the statistical significance of non-annual reversal strategies is eliminated after the risk adjustment.[82] Moreover, Table 5 shows evidence that these findings still hold and that the returns from the annual strategies even increase through time, as the significant annual decile spread based on years 16-20 constantly increases across the three periods, from 0.39% in 1965-1982 to 0.84% in 2000-2016. On the other hand, the decile spreads from both strategies non-annual and all, based on the same years, are mostly negative and not significant.

Furthermore, Table 10 in the appendix contains a heatmap where the largest differences between the risk-adjusted returns from Table 5 and the average returns from the winner-loser strategies reported in Table 4 are highlighted. The decile spreads of the strategies non-annual and all, based on year 1 in the period 1965-1982, increase and become significant. The same occurs for the annual strategy based on year 1 within the period of 2000-2016, where it increases to 0.65%. Overall, the largest decile spread differences refer to strategies based on year 1 and years 2-5, where the risk-adjusted returns mostly

[78] Cf. Schwert, 2003, p.946.
[79] Cf. Fama, French, 1993, p.19-26.
[80] Cf. Fama, French, 1993, p.7f
[81] Cf. Cf. Heston, Sadka, 2008, p.425.
[82] Cf. Heston, Sadka, 2008, p.425-427.

increase, while the decile spreads based on years 6-10, 11-15 and 16-20 do not change substantially. Finally, since the risk-adjusted returns from the decile spreads for annual strategies in 2000-2016 are relatively high and significant for all five intervals, from year 1 until years 16-20, it seems that returns of seasonal strategies are not explained by risk factors.

Table 5. Risk-adjusted returns.

Period	1965-1982			1983-1999			2000-2016		
Portfolio	1	10	10-1	1	10	10-1	1	10	10-1
Year 1									
All	-0.65	0.47	1.12	-1.11	0.23	1.34	-0.47	0.47	0.94
	[-3.08]	[2.23]	[3.31]	[-3.97]	[1.86]	[4.81]	[-0.82]	[2.64]	[1.55]
Annual	-0.80	0.45	1.24	-1.27	0.11	1.39	-0.27	0.39	0.65
	[-5.56]	[2.56]	[5.10]	[-7.13]	[0.69]	[7.82]	[-0.94]	[1.58]	[2.38]
Non Annual	-0.51	0.38	0.89	-0.85	0.16	1.01	-0.42	0.45	0.87
	[-2.13]	[1.71]	[2.37]	[-2.91]	[1.34]	[3.54]	[-0.71]	[2.28]	[1.32]
Years 2-5									
All	0.10	-0.52	-0.62	-0.14	-0.49	-0.35	0.05	0.09	0.04
	[0.46]	[-2.93]	[-1.87]	[-0.38]	[-3.41]	[-0.80]	[0.16]	[0.46]	[0.14]
Annual	-0.38	0.05	0.43	-0.88	0.24	1.12	-0.21	0.41	0.62
	[-2.68]	[0.27]	[1.72]	[-4.80]	[1.56]	[7.09]	[-1.17]	[1.55]	[2.30]
Non Annual	0.24	-0.60	-0.84	-0.01	-0.66	-0.65	0.14	-0.01	-0.15
	[1.14]	[-3.28]	[-2.47]	[-0.03]	[-3.84]	[-1.51]	[0.42]	[-0.07]	[-0.54]
Years 6-10									
All	-0.04	-0.14	-0.09	-0.31	-0.53	-0.22	0.49	-0.13	-0.62
	[-0.28]	[-0.82]	[-0.37]	[-1.85]	[-3.40]	[-1.13]	[3.42]	[-0.55]	[-2.88]
Annual	-0.34	0.30	0.65	-0.68	0.15	0.83	-0.10	0.59	0.69
	[-3.09]	[2.18]	[3.81]	[-4.16]	[0.98]	[4.09]	[-0.90]	[2.71]	[3.75]
Non Annual	0.12	-0.23	-0.35	-0.11	-0.55	-0.44	0.70	-0.21	-0.92
	[0.72]	[-1.38]	[-1.45]	[-0.74]	[-3.64]	[-2.19]	[4.58]	[-0.93]	[-4.83]
Years 11-15									
All	-0.32	0.06	0.37	-0.16	-0.15	0.01	0.59	0.06	-0.53
	[-2.26]	[0.49]	[2.00]	[-1.21]	[-0.99]	[0.06]	[3.08]	[0.32]	[-3.04]
Annual	-0.41	0.46	0.87	-0.66	0.26	0.92	-0.07	0.51	0.58
	[-3.31]	[3.83]	[4.96]	[-4.13]	[1.71]	[5.69]	[-0.38]	[2.58]	[3.77]
Non Annual	-0.08	0.09	0.17	0.08	-0.32	-0.41	0.72	-0.05	-0.77
	[-0.64]	[0.81]	[1.01]	[0.44]	[-1.92]	[-1.77]	[3.41]	[-0.29]	[-3.67]
Years 16-20									
All	0.08	-0.18	-0.26	-0.26	-0.12	0.14	0.26	0.22	-0.04
	[0.54]	[-1.47]	[-1.53]	[-1.91]	[-0.61]	[0.58]	[1.55]	[1.35]	[-0.24]
Annual	-0.28	0.11	0.39	-0.60	0.16	0.76	-0.20	0.64	0.84
	[-3.16]	[1.02]	[2.71]	[-4.02]	[1.12]	[4.74]	[-1.01]	[3.16]	[4.60]
Non Annual	0.09	-0.20	-0.29	-0.16	-0.33	-0.17	0.49	0.10	-0.39
	[0.60]	[-1.63]	[-1.80]	[-1.04]	[-1.60]	[-0.62]	[2.98]	[0.64]	[-2.37]

Source data: CRSP; Fama/French 3 factors

Since the risk factors apparently do not explain the high returns for the seasonal strategies, these anomalies could alternatively be explained by mispricing factors. To verify this,

regressions following the same structure, but using the four factors from Stambaugh and Yuan instead of the three risk factors, are applied next.[83]

5.6 Returns Adjusted for Mispricing

This method consists of regressing the portfolio monthly returns (excess of risk-free rate) on the factors presented in section 4.3, which are: market return (excess of risk-free rate), denoted by RM-RF, size (SMB), MGMT and PERF. The regression is calculated for each portfolio separately and is given in equation 5. The monthly factors are available on the authors' websites, which is indicated in section VII.[84]

(5)[85] $$PR_{jt} - RF_t = a_j + \beta_j(RM_t - RF_t) + s_j SMB_t + m_j MGMT_t + p_j PERF_t + e_{jt}$$

The interception a_j characterizes the portfolio return adjusted for both mispricing factors MGMT and PERF, and for the risk factors SMB and RM-RF. The intercepts from each portfolio and their respective t-statistics are shown in Table 6.

Table 6 indicates that, for the all-months and non-annual strategies based on year 1, all average returns from portfolios 1, 10 and 10-1, for all three periods, are not significant. This is consistent with the hypothesis that their returns are explained by the four factors. However, this does not hold for the annual strategy, where there is only one non-significant (0.05 level) decile spread return, which is in 2000-2016 based on year 1. Similarly, in the years 2-5, 6-10, 11-15 and 16-20, the decile spread returns of the strategies non-annual and all are predominantly not significant, whereas the annual decile spreads are significant.

Moreover, the heatmap in Table 11 in the appendix, which contains the differences between returns adjusted for mispricing and winner-loser returns including delisting, shows that the decile spreads most affected by the four factors are related to shorter-term strategies, based on returns from year 1, and to the strategies all and non-annual. The performance of the annual decile spreads is mostly greater than the returns of the all-months and non-annual decile spreads. Hence, the seasonal strategy seems to be less explained by the four factors than the other two strategies.

[83] Cf. Stambaugh, Yuan, 2017, p.1271.
[84] Cf. Stambaugh, Yuan, 2017, p.1275-1285.
[85] Cf. Stambaugh, Yuan, 2017, p.1283. .

Table 6. Returns adjusted for mispricing.

Period	1965-1982			1983-1999			2000-2016		
Portfolio	1	10	10-1	1	10	10-1	1	10	10-1
Year 1									
All	0.14	-0.18	-0.32	-0.29	-0.01	0.28	0.75	0.30	-0.46
	[0.59]	[-0.81]	[-0.97]	[-0.82]	[-0.03]	[0.81]	[1.29]	[1.26]	[-0.73]
Annual	-0.68	0.43	1.12	-1.11	0.28	1.39	0.20	0.79	0.59
	[-3.52]	[2.21]	[4.29]	[-4.23]	[1.53]	[6.13]	[0.74]	[2.52]	[1.84]
Non Annual	0.27	-0.29	-0.56	0.00	-0.05	-0.05	0.83	0.22	-0.61
	[1.01]	[-1.31]	[-1.55]	[0.01]	[-0.23]	[-0.14]	[1.35]	[0.90]	[-0.86]
Years 2-5									
All	-0.11	-0.32	-0.21	0.15	-0.21	-0.36	0.65	0.36	-0.29
	[-0.39]	[-1.81]	[-0.62]	[0.32]	[-1.33]	[-0.72]	[1.74]	[1.66]	[-0.87]
Annual	-0.42	0.15	0.57	-0.74	0.57	1.31	0.05	0.66	0.60
	[-2.09]	[0.89]	[2.40]	[-3.12]	[3.09]	[6.46]	[0.24]	[2.36]	[1.98]
Non Annual	0.01	-0.40	-0.42	0.31	-0.33	-0.64	0.77	0.23	-0.55
	[0.05]	[-2.22]	[-1.20]	[0.72]	[-2.30]	[-1.37]	[1.99]	[1.16]	[-1.82]
Years 6-10									
All	-0.19	-0.02	0.17	-0.15	-0.42	-0.26	0.55	0.18	-0.37
	[-1.32]	[-0.15]	[0.76]	[-0.69]	[-2.38]	[-1.07]	[3.09]	[0.74]	[-1.72]
Annual	-0.35	0.23	0.59	-0.55	0.31	0.86	-0.09	0.84	0.93
	[-2.42]	[1.66]	[2.89]	[-2.80]	[1.63]	[3.42]	[-0.55]	[3.37]	[3.92]
Non Annual	-0.03	-0.08	-0.06	0.03	-0.44	-0.48	0.82	0.09	-0.73
	[-0.19]	[-0.56]	[-0.26]	[0.15]	[-2.76]	[-1.79]	[4.30]	[0.39]	[-3.73]
Years 11-15									
All	-0.08	-0.06	0.02	0.03	-0.01	-0.04	0.73	0.22	-0.51
	[-0.45]	[-0.66]	[0.13]	[0.16]	[-0.07]	[-0.21]	[3.06]	[1.24]	[-2.96]
Annual	-0.39	0.42	0.81	-0.63	0.54	1.16	0.10	0.68	0.58
	[-2.33]	[3.44]	[4.05]	[-2.79]	[2.75]	[4.87]	[0.51]	[2.77]	[2.84]
Non Annual	0.13	-0.01	-0.14	0.38	-0.24	-0.62	0.90	0.13	-0.77
	[0.73]	[-0.11]	[-0.84]	[1.61]	[-1.22]	[-2.07]	[3.40]	[0.72]	[-3.44]
Years 16-20									
All	0.10	-0.09	-0.19	-0.29	-0.02	0.28	0.46	0.32	-0.14
	[0.60]	[-0.54]	[-1.04]	[-1.40]	[-0.09]	[1.09]	[2.14]	[1.80]	[-0.80]
Annual	-0.32	0.21	0.53	-0.59	0.28	0.87	-0.09	0.87	0.95
	[-2.36]	[1.54]	[2.83]	[-3.58]	[1.96]	[4.80]	[-0.37]	[3.80]	[4.46]
Non Annual	0.11	-0.13	-0.24	-0.19	-0.27	-0.09	0.74	0.18	-0.56
	[0.71]	[-0.74]	[-1.38]	[-0.76]	[-1.20]	[-0.26]	[3.79]	[1.18]	[-3.11]

Source data: CRSP; Stambaugh-Yuan Mispricing Factors

In summary, even though most of the adjusted returns of the decile spreads from the strategies all and non-annual decrease substantially or become statistically insignificant, the adjusted decile spread performance of the annual strategy persists significant and greater than 50 basis points for almost all periods and yearly intervals.

The evidence presented so far, that annual strategies achieve mostly high returns, even after controlling them for risk and mispricing factors, raises the question which is discussed in the next section.

6 Why do Investors not Arbitrage Away the Abnormal Returns?

McLean and Potiff suggest in 2016, that when an academic research about trading strategies is publicized, the abnormal returns originated through the strategies tend to shrink substantially in out-of-sample and post-publication periods, partly due to greater activity from sophisticated traders.[86] This is partially consistent with the results from this study, where risk-adjusted returns from 2000-2016 are compared with returns within the two previous periods (1965-1982 and 1983-1999), which are completely included in the sample originally analyzed by Heston and Sadka in 2008 (1965-2002).[87] The risk-adjusted returns of the decile spreads from the annual strategies for years 1, 2-5 and 11-15, decrease in the period 2000-2016 in comparison to 1983-1999. However, those returns are still positive, larger than 50 basis points and significant. Furthermore, this does not apply for the years 16-20, where the risk-adjusted return from the annual decile spread constantly increases until it reaches 84 basis points in 2000-2016.

To explain those remaining returns, there is evidence that some momentum strategies which appear lucrative may not result in profit after the inclusion of transaction costs, especially for equally-weighted portfolios, such as the ones empirically applied in this study.[88] However, for strategies that weight portfolios according to value or liquidity, the inclusion of the costs still does not exclude the abnormal effect, which remains a puzzle.[89] In the case of this study, it is reasonable to assume that rebalancing the complete portfolio each month generates substantial costs, which may lead to losses even if the monthly returns reach 60 to 70 basis points.[90]

7 Conclusion

This study shows empirically that, for the period between 2000 and 2016, seasonal momentum effects persist when the portfolio is formed based on returns from the same calendar month from 6 to 20 years in the past. The achieved average returns from the annual decile spreads exceed 58 basis points for this period, even after controlling for risk

[86] Cf. McLean, Pontiff, 2016, p.28f.
[87] Cf. Heston, Sadka, 2008, p.426.
[88] Cf. Korajczyk, Sadka, 2004, p.1071f.
[89] Cf. Korajczyk, Sadka, 2004, p.1071f.
[90] Cf. Heston, Sadka, 2008, p.443.

and mispricing factors. Moreover, in the two earlier periods 1965-1982 and 1983-1999, the high decile-spread returns from annual strategies persist even when the past-performance analyzed for portfolio formation occurred in shorter-term intervals, from one to five years in the past. At the same time, strategies based on past-returns from all other months present mostly low or statistically insignificant decile-spread performance.

The implications of these findings are that seasonal momentum remains a puzzle, which is not explained by factors that usually explain other types of momentum and contrarian effects. Besides, since empirical evidence indicates that strategies based solely on past-performance achieve high returns, market efficiency in its weak form might be violated.

However, some limitations of this study could be explored in a future research for more refined results. For instance, all stocks are equally weighted in each portfolio, although different weights could be implemented with the purpose of maximizing the performance. Furthermore, transaction costs are not considered in the winner-loser strategies presented in this thesis, although they might influence the results considerably, due to the frequent portfolio rebalancing. Hence, the inclusion of transaction costs into the model can contribute to finding in which extent the high returns can be converted into profit.

V Appendix

Table 7. Simple cross-sectional regressions of returns: sample comparison.

	1965-2002		1965-2016		2003-2016	
Lag	Estimate	t-statistic	Estimate	t-statistic	Estimate	t-statistic
1	-5.44	-8.67	-4.34	-8.20	-1.39	-2.70
2	-0.05	-0.12	0.15	0.38	0.70	0.80
3	1.24	3.26	1.03	2.92	0.45	0.59
4	0.63	1.46	0.50	1.44	0.17	0.27
5	0.90	2.11	0.66	1.72	-0.01	-0.01
6	1.02	2.38	0.76	1.68	0.04	0.03
7	1.10	3.13	0.78	2.30	-0.08	-0.10
8	0.64	1.42	0.68	1.85	0.79	1.22
9	1.25	3.03	0.80	2.03	-0.43	-0.56
10	0.84	2.53	0.47	1.27	-0.54	-0.52
11	1.45	3.86	1.45	3.77	1.44	1.38
12	2.89	8.00	2.21	6.66	0.37	0.62
24	1.35	3.85	1.26	3.97	0.99	1.46
36	1.27	3.47	1.18	3.48	0.94	1.22
48	1.48	3.46	1.05	2.91	-0.10	-0.15
60	0.57	1.31	0.27	0.72	-0.55	-0.85
72	1.32	3.72	1.34	4.54	1.39	2.64
84	1.14	3.51	0.86	3.19	0.10	0.23
96	0.95	2.18	1.07	3.13	1.39	3.22
108	1.24	3.37	0.98	3.25	0.28	0.64
120	1.29	4.13	1.21	4.45	1.00	1.88
132	1.59	5.05	1.28	4.33	0.43	0.68
144	1.24	3.51	1.07	3.86	0.60	1.72
156	0.73	2.04	0.80	2.41	0.99	1.34
168	0.92	2.15	0.99	2.91	1.18	2.68
180	1.36	3.51	1.20	3.90	0.75	2.14
192	1.65	3.38	1.37	3.44	0.62	1.07
204	1.40	3.71	1.35	4.28	1.20	2.18
216	1.23	2.88	1.19	3.46	1.08	2.03
228	-0.04	-0.09	0.23	0.64	0.95	1.89
240	1.17	3.01	1.14	3.71	1.07	2.37

Source data: CRSP

Table 8. Heatmap: WL returns incl. delisting minus WL excl. delisting.

Period	1965-1982			1983-1999			2000-2016		
Portfolio	1	10	10-1	1	10	10-1	1	10	10-1
Year 1									
All	-0.09	-0.01	0.08	-0.27	-0.03	0.24	-0.44	-0.05	0.39
Annual	-0.05	-0.03	0.02	-0.18	-0.06	0.13	-0.23	-0.09	0.14
Non Annual	-0.09	0.00	0.09	-0.28	-0.03	0.25	-0.43	-0.05	0.38
Years 2-5									
All	-0.06	-0.02	0.04	-0.24	-0.03	0.21	-0.30	-0.04	0.26
Annual	-0.04	-0.05	-0.02	-0.12	-0.07	0.06	-0.15	-0.08	0.07
Non Annual	-0.06	-0.02	0.04	-0.25	-0.03	0.22	-0.28	-0.04	0.24
Years 6-10									
All	0.00	0.00	0.00	-0.13	-0.05	0.08	-0.10	-0.06	0.04
Annual	-0.02	-0.01	0.00	-0.08	-0.06	0.02	-0.09	-0.07	0.02
Non Annual	0.00	0.00	0.01	-0.12	-0.03	0.09	-0.09	-0.06	0.03
Years 11-15									
All	0.01	0.00	-0.01	-0.06	-0.05	0.01	-0.05	-0.07	-0.03
Annual	0.00	0.00	0.01	-0.05	-0.02	0.03	-0.05	-0.07	-0.02
Non Annual	0.02	0.00	-0.03	-0.06	-0.05	0.00	-0.07	-0.08	-0.02
Years 16-20									
All	0.00	0.00	0.00	-0.02	-0.04	-0.02	-0.04	-0.07	-0.03
Annual	0.01	0.00	-0.01	-0.03	-0.02	0.02	-0.06	-0.07	-0.01
Non Annual	-0.01	-0.01	0.00	-0.01	-0.04	-0.02	-0.04	-0.07	-0.03

Source data: CRSP

Table 9. Winner-loser incl. delisting returns with -100% for omitted values.

Period	1965-1982			1983-1999			2000-2016		
Portfolio	1	10	10-1	1	10	10-1	1	10	10-1
Year 1									
All	1.26	1.84	0.58	0.49	1.61	1.12	0.66	1.24	0.58
	[2.05]	[3.31]	[1.49]	[1.13]	[4.44]	[3.66]	[0.80]	[2.60]	[0.88]
Annual	0.82	2.13	1.31	0.17	1.61	1.45	0.74	1.19	0.45
	[1.39]	[3.48]	[5.34]	[0.50]	[4.34]	[6.93]	[1.26]	[2.45]	[1.80]
Non Annual	1.49	1.69	0.21	0.75	1.53	0.78	0.69	1.23	0.54
	[2.31]	[3.08]	[0.46]	[1.64]	[4.45]	[2.35]	[0.84]	[2.61]	[0.79]
Years 2-5									
All	2.01	0.63	-1.37	1.33	0.93	-0.40	1.18	0.84	-0.34
	[3.91]	[1.11]	[-4.99]	[2.86]	[2.84]	[-0.98]	[1.81]	[1.74]	[-0.81]
Annual	1.12	1.66	0.53	0.48	1.72	1.24	0.71	1.25	0.53
	[2.05]	[2.94]	[1.95]	[1.35]	[5.37]	[6.67]	[1.40]	[2.63]	[1.89]
Non Annual	2.17	0.53	-1.64	1.50	0.76	-0.73	1.27	0.72	-0.55
	[4.14]	[0.93]	[-6.00]	[3.29]	[2.32]	[-1.93]	[1.90]	[1.48]	[-1.28]
Years 6-10									
All	1.39	1.25	-0.14	1.17	0.90	-0.28	1.30	0.77	-0.53
	[2.87]	[2.50]	[-0.61]	[3.48]	[2.77]	[-1.17]	[2.94]	[1.60]	[-2.85]
Annual	0.95	1.80	0.85	0.76	1.55	0.79	0.73	1.44	0.71
	[1.89]	[4.13]	[5.45]	[2.61]	[4.59]	[4.30]	[1.66]	[3.18]	[3.72]
Non Annual	1.58	1.17	-0.41	1.34	0.86	-0.48	1.50	0.68	-0.82
	[3.27]	[2.25]	[-1.87]	[3.89]	[2.68]	[-1.86]	[3.53]	[1.47]	[-4.99]
Years 11-15									
All	1.08	1.29	0.21	1.26	1.30	0.04	1.35	0.92	-0.43
	[2.62]	[2.94]	[0.89]	[3.90]	[4.43]	[0.20]	[3.10]	[2.17]	[-2.38]
Annual	0.82	1.77	0.95	0.78	1.65	0.87	0.75	1.35	0.59
	[1.99]	[4.06]	[5.60]	[2.48]	[5.82]	[6.52]	[1.71]	[3.17]	[3.59]
Non Annual	1.31	1.31	0.01	1.47	1.13	-0.34	1.49	0.82	-0.66
	[3.31]	[2.99]	[0.03]	[4.61]	[3.65]	[-1.63]	[3.45]	[1.94]	[-3.32]
Years 16-20									
All	1.43	0.94	-0.48	1.21	1.32	0.11	1.08	1.09	0.01
	[3.41]	[2.46]	[-2.34]	[4.11]	[4.89]	[0.53]	[2.57]	[2.47]	[0.06]
Annual	0.90	1.38	0.48	0.77	1.59	0.82	0.63	1.42	0.79
	[2.17]	[3.57]	[2.71]	[2.65]	[5.42]	[4.08]	[1.36]	[3.70]	[4.27]
Non Annual	1.48	0.92	-0.56	1.34	1.09	-0.26	1.28	0.96	-0.32
	[3.52]	[2.51]	[-2.92]	[4.17]	[3.86]	[-0.95]	[3.16]	[2.21]	[-1.87]

Source data: CRSP

Table 10. Heatmap: risk-adjusted returns minus WL-returns incl. delisting.

Period	1965-1982			1983-1999			2000-2016		
Portfolio	1	10	10-1	1	10	10-1	1	10	10-1
Year 1									
All	-1.92	-1.37	0.55	-1.60	-1.38	0.22	-1.13	-0.77	0.36
Annual	-1.62	-1.68	-0.06	-1.44	-1.50	-0.06	-1.01	-0.80	0.21
Non Annual	-2.00	-1.32	0.68	-1.60	-1.37	0.23	-1.11	-0.79	0.32
Years 2-5									
All	-1.91	-1.15	0.75	-1.48	-1.43	0.05	-1.14	-0.75	0.38
Annual	-1.51	-1.61	-0.10	-1.36	-1.48	-0.13	-0.93	-0.84	0.09
Non Annual	-1.93	-1.13	0.81	-1.51	-1.43	0.09	-1.13	-0.73	0.40
Years 6-10									
All	-1.44	-1.39	0.05	-1.48	-1.42	0.06	-0.81	-0.90	-0.09
Annual	-1.30	-1.50	-0.20	-1.44	-1.41	0.03	-0.83	-0.85	-0.02
Non Annual	-1.46	-1.40	0.06	-1.46	-1.42	0.04	-0.80	-0.90	-0.10
Years 11-15									
All	-1.40	-1.24	0.16	-1.43	-1.45	-0.03	-0.76	-0.87	-0.11
Annual	-1.24	-1.32	-0.08	-1.44	-1.39	0.05	-0.82	-0.83	-0.01
Non Annual	-1.39	-1.22	0.17	-1.39	-1.45	-0.06	-0.77	-0.88	-0.11
Years 16-20									
All	-1.35	-1.12	0.23	-1.46	-1.44	0.02	-0.82	-0.87	-0.05
Annual	-1.18	-1.27	-0.10	-1.38	-1.43	-0.06	-0.83	-0.78	0.05
Non Annual	-1.39	-1.13	0.26	-1.50	-1.41	0.09	-0.79	-0.86	-0.07

Source data: CRSP; Fama/French 3 factors

Table 11. Heatmap: return adjusted for mispricing minus WL-return incl. delisting.

Period	1965-1982			1983-1999			2000-2016		
Portfolio	1	10	10-1	1	10	10-1	1	10	10-1
Year 1									
All	-1.13	-2.02	-0.89	-0.78	-1.61	-0.84	0.10	-0.94	-1.04
Annual	-1.50	-1.69	-0.19	-1.28	-1.33	-0.06	-0.54	-0.40	0.14
Non Annual	-1.22	-1.99	-0.77	-0.75	-1.58	-0.83	0.14	-1.01	-1.15
Years 2-5									
All	-2.11	-0.95	1.17	-1.19	-1.15	0.04	-0.53	-0.48	0.05
Annual	-1.54	-1.50	0.03	-1.22	-1.16	0.06	-0.66	-0.59	0.07
Non Annual	-2.16	-0.93	1.23	-1.19	-1.09	0.09	-0.50	-0.50	0.00
Years 6-10									
All	-1.58	-1.28	0.31	-1.32	-1.31	0.01	-0.75	-0.59	0.16
Annual	-1.31	-1.57	-0.26	-1.30	-1.24	0.06	-0.82	-0.59	0.23
Non Annual	-1.61	-1.25	0.35	-1.31	-1.30	0.00	-0.68	-0.59	0.09
Years 11-15									
All	-1.16	-1.35	-0.19	-1.23	-1.31	-0.08	-0.62	-0.71	-0.08
Annual	-1.21	-1.36	-0.15	-1.40	-1.11	0.29	-0.66	-0.67	-0.01
Non Annual	-1.18	-1.32	-0.15	-1.09	-1.37	-0.28	-0.58	-0.70	-0.11
Years 16-20									
All	-1.33	-1.03	0.30	-1.50	-1.34	0.16	-0.62	-0.77	-0.15
Annual	-1.22	-1.18	0.04	-1.36	-1.31	0.05	-0.71	-0.55	0.16
Non Annual	-1.37	-1.05	0.32	-1.53	-1.36	0.17	-0.54	-0.77	-0.24

Source data: CRSP; Stambaugh-Yuan Mispricing Factors

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VII Used Tools and Datasets (Benutzte Hilfsmittel)

Tools

Microsoft Excel (2016).

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Datasets

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VIII Honorable Declaration (Ehrenwörtliche Erklärung)

„Ich versichere hiermit, dass ich die vorliegende Arbeit selbständig und ohne Benutzung anderer als der angegebenen Quellen und Hilfsmittel verfasst habe. Wörtlich übernommene Sätze oder Satzteile sind als Zitat belegt, andere Anlehnungen, hinsichtlich Aussage und Umfang, unter Quellenangabe kenntlich gemacht. Die Arbeit hat in gleicher oder ähnlicher Form noch keiner Prüfungsbehörde vorgelegen und ist nicht veröffentlicht. Sie wurde nicht, auch nicht auszugsweise, für eine andere Prüfungs- oder Studienleistung verwendet. Zudem versichere ich, dass die von mir abgegebenen schriftlichen (gebundenen) Versionen meiner Bachelorarbeit mit der abgegebenen elektronischen Version auf einem Datenträger inhaltlich übereinstimmen.“

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