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Topic:

Time-Series versus Cross-Sectional Momentum

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Abstract

We empirically examine the differences between time-series and cross-sectional momentum based on the stocks included in the German Prime All Share Index. Our method is mainly based on the findings of Goyal and Jegadeesh (2017) and Kim et al. (2016). In particular, we examine the relevance of volatility scaling and net-long positions for comparing the two momentum strategies. With equally-sized long and short positions, we observe cross-sectional momentum outperforming time-series momentum for a sample period from 1996 to 2018. Net-long positions and volatility scaling contribute both to even higher returns. However, we find that not the weighting in volatility scaling, but the time-varying investment into risky assets causes significant changes in returns. All in all, no unequivocal evidence for the superiority of the time-series momentum could be determined suggesting that abnormal returns in the study of Moskowitz et al. (2012) were not due to the anomaly itself.

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List of Abbreviations and Acronyms

CS^{TS}	time-varying cross-sectional momentum strategy with the long positions set equal in size to the long positions of the time-varying time-series momentum strategy.
CS^{TVM}	cross-sectional momentum strategy with time-varying investment into the market.
TS^{TVM}	time-series momentum strategy with time-varying investment into the market.
BAH	buy-and-hold.
CAPM	Capital Asset Pricing Model.
const	constellation.
CRSP	Center for Research in Security Prices.
CS	cross-sectional.
DD	maximum drawdown.
Kurt	kurtosis.
Nr.	Number.
p.	page.
RP	risk parity.
sc.	scaled.
SD	standard deviation.
Skew	skewness.
SR	Sharpe ratio.
TS	time-series.
TV	time-varying.

List of Symbols

α_{CAPM}	In a CAPM regression obtained alpha of considered strategy.
α^{l}_{CAPM}	In a CAPM regression obtained alpha of considered levered strategy.
α^{u}_{CAPM}	In a CAPM regression obtained alpha of considered unlevered strategy.
α_{FF3}	In the Fama and French (1993) three-factor model obtained alpha of considered strategy.
β_i	Regression coefficient.
β_{const}	Slope coefficients of a regression for constellation $const$.
ε_t	Error term of regression.
HML_t	Factor related to the book-to-market ratio of the portfolio in time t.
$€LongCS$	Euro amount of long investments into risky assets as calculated by the time-varying cross-sectional momentum following strategy.
$€Long$	Euro amount of long investments into risky assets.
$€Long^{l}$	Euro amount of levered long investments into risky assets.
$€LongTS$	Euro amount of long investments into risky assets as calculated by the time-varying time-series momentum following strategy.
$€Long^{u}$	Euro amount of unlevered long investments into risky assets.
N	Number of stocks in the portfolio.
N^{+}	Number of long positions in portfolio.
N^{-}	Number of short positions in portfolio.
$NetLong^{TS}_t$	Net-long position of the time series momentum strategy in period t.
R^2	Coefficient of determination.
$\bar{R}_t$	Cross-sectional equal-weighted average of the holding period returns.
R_{it-1}	Excess return of the i^{th} stock in the ranking period.
R_{it}	Excess return of the i^{th} stock in the holding period.
$\bar{R}^{scaled}_t$	Scaled market index.

R_t^{strat}	Excess return of the portfolio based on the strategy $strat$ with the holding period starting in month t.
$R_t^{CS_{TVM}}$	Excess return of the portfolio based on cross-sectional momentum with the holding period starting in month t and additional time-varying investment in the equal-weighted index.
$€Short$	Euro amount of short positions of risky assets.
σ_{it}	Exponentially weighted average of lagged squared daily returns until period t.
SMB_t	Size factor of the portfolio in time t.
th_{strat}	Threshold of the portfolio based on strategy $strat$.
$€Total$	Euro amount of levered long and short investments into risky assets.

1 Introduction

In 1993, Jegadeesh and Titman discovered a pattern called cross-sectional (CS) momentum. CS momentum means that a stock outperforming its peers in the past is likely to continue to outperform them in the future. In 2012, Moskowitz et al. examine a different pattern, the time-series (TS) momentum. TS momentum works similarly to its CS counterpart, but concentrates on the stock's individual performance and not on the peer's performance (Moskowitz et al., 2012). Both patterns have the potential to threat the random walk hypothesis, one well-known assumption in the field of financial research, which states that one cannot predict the future price of an asset by knowing only its past prices (Fama, 1995). This highlights the importance of understanding these anomalies.

The first step to a deeper apprehension of the market mechanisms leading to momentum is to define the term *momentum* itself. Moskowitz et al. (2012) expose TS momentum as the actual anomaly literature should study. Goyal and Jegadeesh (2017), however, argue that the conclusions of Moskowitz et al. (2012) are contaminated by a profitable construction of the TS portfolios compared to the CS portfolio: volatility weighting and positive net-long positions allegedly embellish TS returns.

Regarding the lack of literature critically assessing the sources of differences between the momentum strategies on the German stock market, this paper aims to analyze the differences of TS and CS momentum portfolios of the Prime All Share Index by assessing the hypothesis whether TS momentum outperforms CS momentum.

In order to achieve this objective we will continue as follows. Section 2 gives an overview of the relevant literature, including the role of behavioral theories. The data sources and applied methods are described in Section 3, before Section 4 outlines our empirical analysis testing the relevance of the weighting of long and short side, the role of volatility scaling and the differences in transaction costs. Furthermore, restrictions to our empirical study are outlined. Section 5 concludes.

2 Literature Overview

Since its discovery in the early 1990s, a wide range of literature was published discussing momentum. Especially, two different forms of this anomaly prevail: the CS momentum on the one hand, and the TS momentum on the other hand. This section serves to provide an overview of the corresponding publications.

Already in 1993, evidence for CS momentum on the New York and American Stock Exchange was conceived by Jegadeesh and Titman (1993)[1]. First, they rank their sample stocks by returns in a ranking period with a predefined length. Subsequently, they go long in the top decile serving as "winner" portfolio and short the bottom decile portfolio serving as "losers" in the holding period. This decile strategy renders average returns of up to 12.01%. Many authors follow their example and scrutinize this pattern. For instance, Moskowitz and Grinblatt (1999) detect that a huge part of the success of momentum strategies arises from industry momentum.

Jegadeesh and Titman (2002) delved into the inquiry whether cross-sectional differences in unconditional expected returns could explain momentum profits. The employed data was derived from the New York Stock Exchange and the American Stock Exchange covering a sample period from 1965 to 1997. In their paper, Jegadeesh and Titman (2002) highlight the small sample bias in a bootstrap experiment conducted by Conrad and Kaul (1998), who state the thesis that cross-sectional and not time-series differences in unconditional expected returns explain momentum profits. Jegadeesh and Titman (2002) present an unbiased variation of this bootstrap experiment and discern that in contrast to the thesis by Conrad and Kaul (1998), the cross-sectional differences do not account for much of the momentum profits undermining CS momentum.

[1] Their analysis comprises the period from 1965 to 1989.

Moskowitz et al. (2012) analyze the TS momentum effect with data on 12 different cross-currency pairs, futures prices for 24 commodities, 9 developed equity indices and 13 developed government bond futures for a sample period from January 1965 to December 2009. In order to ensure comparability within their data set, the authors scale the returns by the respective asset volatility. Moskowitz et al. (2012) discover that a portfolio exploiting time series momentum achieves significant alphas of up to 6.61% for the 1×6 constellation.[2] Furthermore, Moskowitz et al. (2012) show that TS momentum explains CS momentum by regressing the returns attained by TS strategies on the returns of CS strategies with an R^2 of up to 56%. Evidence for the importance of stock's individual performance was also received by other authors. Grundy and Martin (2001) perform an empirical analysis to discover the factor loadings of different strategies, using inter alia the three-factor model of Fama and French (1993). They show that a strategy which hinges its ranking decision on stock-specific returns is more successful than basing this decision on total returns. He and Li (2015) examine the profitability of TS momentum strategies using a model of investor behaviour with fundamental, contrarian and momentum traders who show different expectations in price behaviour. The authors discover that the momentum strategy is profitable in the short term only in with momentum traders dominated markets. Baltas and Kosowski (2013) want to identify whether there is an existent link between TS momentum strategies and commodity trading advisors fund performance. Using 71 future contracts across all asset classes from December 1974 to January 2012, they apply the method of Moskowitz et al. (2012), including volatility scaling, to form a time series momentum strategy. Baltas and Kosowski (2013) notice strong TS momentum and that strategies with different frequencies of re-balancing do not correlate. Based on a time series analysis, the authors expose the use of momentum strategies as the success factor of commodity trading advisors funds.

[2] Due to continuity reasons, we use the notation introduced by Goyal and Jegadeesh (2017) to describe the time frame of the strategies: a $r \times h$-strategy bases the ranking of stocks on the returns of the prior r months, and holds the stocks for h months afterwards.

Upon rebuilding the portfolios analyzed by Moskowitz et al. (2012), Kim et al. (2016) uncover volatility scaling, and not TS momentum, as the true source of abnormal returns. They further note that the results of Menkhoff et al. (2012), who document higher returns for their TS portfolio than for their CS portfolio, root from the missing volatility scaling entailing the disparate results of Moskowitz et al. (2012) and Menkhoff et al. (2012). Additionally, Kim et al. (2016) deal with the performance of TS and CS strategies in relation to the effect of volatility scaling and different sub-periods. They discern that the TS strategy needs to be volatility scaled in order to beat the CS and buy-and-hold strategy in the sub-period from 1985 to 2009. Both the scaled and the unscaled TS momentum strategy do not explain significantly the returns achieved after the financial crisis in the sub-period ranging from 2009 to 2013. The utilized data consists of daily settlement prices for 55 futures markets[3] in a sample period from January 1984 to December 2013.

Likewise Kim et al. (2016), other researchers point out the relevance of volatility scaling, also outside of the context of momentum strategies. Asness et al. (2012) deal with risk parity (RP) investing and aim to provide empirical evidence for diverse countries and distinct assets. RP investing means to balance the portfolios in terms of risk. Consequently, volatility scaling effectively makes use of a similar approach to RP investing, as Kim et al. (2016) conclude. Asness et al. (2012) compare the total cumulative returns of different strategies in a sample period from January 1926 to January 2010 and ascertain that RP investing is superior to the market portfolio. They explain their findings by the fact that RP leads to an overproportional share of safer assets in portfolios, which goes along with investors' leverage aversion. Barroso and Santa-Clara (2015) discuss volatility scaling in the context of momentum. They use the realized variances of daily returns to measure the risk of momentum. As momentum has a high Sharpe ratio, but also incorporates a big risk of crashing (e.g. in 2009, there was a huge momentum crash with a loss of up to -73.42% in three

[3] Kim et al. (2016) rebuild the data used by Moskowitz et al. (2012), but exclude e.g. cross-rate currency contracts.

months), it would be beneficial to find a strategy to manage this risk. Barroso and Santa-Clara (2015) try to develop such a strategy: They use the realized volatility to scale the portfolio in order to achieve a strategy with constant volatility. As a result, the Sharpe Ratio increases from 0.53 to 0.97, the excess kurtosis cuts back from 18.24 to 2.68, and the left skew declines from 2.47 to 0.42. Summarizing, volatility scaling improves the success of momentum strategies. One possible explanation for this pattern is the time-varying systematic risk of the momentum strategy. Grundy and Martin (2001) find out that momentum possesses negative beta after times with bad market development. In order to counter this effect, they suggest to hedge the time-varying systematic risk. Daniel and Moskowitz (2016) show that this strategy is not successful in managing the risk of crashes. Going along with that, Barroso and Santa-Clara (2015) explain that 77% of the risk of momentum can be attributed to the strategy and not to the market component. To this extent, scaling with betas and hedging with time-varying betas does not work, because these methods do not deal with the major part of this risk. All in all, Barroso and Santa-Clara (2015) conclude that momentum is not "a dead anomaly"[4], but showed that the recent bad performance was due to high-risk exposure.

In contrast, Baltas and Kosowski (2017) want to demystify the influence of the design of a time-series momentum strategy on the return and turnover. They use futures data on 56 assets (among the assets commodities, equity indices, currencies and government bonds can be found) for a period between January 1983 and February 2013. They conduct an empirical analysis on effects of different volatility estimators and trading rules on turnover and performance. This study shows that using more efficient volatility estimators to scale the assets and using alternative trading rules to identify price trends reduces trading volume without triggering bad performance.

While Kim et al. (2016) identify volatility scaling as the main contribution to the abnormal TS returns of Moskowitz et al. (2012), Goyal and Jegadeesh (2017) pinpoint

[4] See Barroso and Santa-Clara (2015), p. 112.

an additional potential reason: net-long positions. A net-long position is defined as the difference of the long and short side of a portfolio.[5] They use a sample of stocks from the database of the Center for Research in Security Prices (CRSP) and define 1946 to 2013 as the sample period. Furthermore, similar to Kim et al. (2016), they use daily settlement prices for 55 futures markets covering a period from 1985 to 2013. Goyal and Jegadeesh (2017) apply a threshold strategy, meaning that the classification of assets as "winner" or "loser" depends on whether they achieve returns above the average return or not. The authors introduce a strategy they call cross-sectional momentum strategy with time-varying investment into the market (CS^{TVM}), which shall compensate for the net-long investment of the TS strategy. Their main result is that the difference between TS and CS strategies prevails because of the net-long investment of TS strategies: The difference between the excess returns of TS and CS^{TVM} is only 0,51% for the 60×60 constellation, and almost all of the differences for the various combinations of ranking period and holding period are insignificant at the 95% level. If the market performs well, then this net-long investment leads to a better performance of TS-strategies as defined by Moskowitz et al. (2012). In our work, we focus on Goyal and Jegadeesh (2017) due to the relevance of their findings in context of the papers of the authors mentioned above.

As mentioned above, beside other aspects, Kim et al. (2016) also document the bad performance of momentum after the financial crisis. Cooper et al. (2004) test whether overreaction leads to momentum and reversal. The condition of the market is important for the profits of momentum strategies: A momentum portfolio over 6 months is only successful after good market conditions. This fits with the overreaction theory. The higher the lagged market return, the higher the momentum profits, but at a certain point, the profits decline. The authors additionally find that

[5] Momentum strategies are in fact zero investments and have thereby long and short positions of an equal size, as each long/short position in a stock goes along with an equal-sized short/long position in the risk-free rate. However, we will only refer to the risky long and short positions from now on.

momentum profits reverse in the long run. This happens even after recessions, where no momentum can be observed, so the reversal once more has other reasons beside momentum. Macroeconomic factors do not account for momentum profits. In contrast, Baltas and Kosowski (2017) identify the increased pairwise correlations as an explanation for the bad performance of momentum strategies after 2008.

Daniel and Moskowitz (2016) come to know that there is a premium on the price of stocks with a bad performance in the past during bad market conditions with high volatility. When the market improves, the losers rise in price, what leads to a crash of the momentum strategies. In such manner, the momentum works inversely in situations like this than it normally does. They demonstrate that the observed variation in momentum premium is not captured by the time-varying volatility risk. The results of Cooper et al. (2004) and Stivers and Sun (2010) complement the results of Daniel and Moskowitz (2016). As explained above, Cooper et al. (2004) want to test the overreaction hypothesis of the momentum and reversal mechanism. Stivers and Sun (2010) notice that changes in the cross-sectional return variation can affect the alteration of momentum premiums. The authors support the rational explanations and not the behavioural ones, considering the connection of the return premiums with the return dispersion.

Another important aspect is to test whether momentum really is a profitable strategy for the investors, if one includes market frictions into the analysis. Exemplary, Korajczyk and Sadka (2004) aim to elucidate whether momentum strategies are still profitable, if one accounts for trading costs. They disclose that the majority of studied strategies i still leading to profits. Keeping the price impact in mind, it is of advantage to use value weighting and not equal weighting. Regarding the relevance of their results, in our empirical analysis we will also shed light on the effects of turnover on profitability of momentum strategies. As our work among other aspects also aims to assess differences between momentum strategies on the German stock market in order to contribute to the literature analyzing country-specific momentum patterns, it is of interest to provide an overview of relevant findings in this field of research. Chaves (2012) develops a new calculation of momentum that reduces volatility and losses of momentum strategies. Using his method, stocks are ranked by their idiosyncratic performance. His results hold in Japan as well, in contrast those of Asness et al. (2013), who do not detect momentum in this country. Similarly to our study, Schiereck et al. (1999) compare momentum strategies applied on the American market to those conducted on all major companies listed on the Frankfurt Stock Exchange for a sample period from 1961 to 1991. The results show that momentum strategies beat passive investing into the market. From a behavioural perspective, it is interesting that the results obtained for the German market are compatible to the US-results despite the cultural differences between the two countries.

The literature has not only focused on providing empirical evidence for the momentum strategies, but also on developing theoretical models explaining these anomalies. Exemplary, De Bondt and Thaler (1995) especially deal with overreaction and biased forecasts. Several researchers focus on individual stocks, leading Moskowitz et al. (2012) to conclude that they are relevant for forecasting TS momentum returns. Barberis et al. (1998) construct a model, where investors develop assumptions corresponding with under- and overreaction. In their model, there is a risk neutral investor, who thinks that the behaviour of the earnings of one asset varies between two states, namely reversion or trending of earnings. As a matter of fact, those earnings change coincidentally. Overreaction is formed, when the price comes to rise several times and the investor assumes that those earnings trend. Despite the argument of Moskowitz et al. (2012), Goyal and Jegadeesh (2017) point out the shortcomings of this theories in predicting TS returns: The model does not incorporate the contribution to returns by the investment in the market due to general correlation structures of the assets. According to Goyal and Jegadeesh (2017), CS momentum strategies are preferable for assessing the quality of the behavioral theories. Especially the fact that these theories mostly base on inappropriate valuation fits with the role of stock-specific returns for CS momentum.

In the next section, we introduce our empirical study.

3 Data and Methodology

We describe briefly the various data sources used in our analysis. Similarly to Goyal and Jegadeesh (2017), who examine whether the findings of Moskowitz et al. (2012) hold for individual U.S. stocks, we analyze momentum strategies for the German stock market. In order to eschew the influence of micro-cap stocks, only stocks included in the Prime All Share Index[6] on the 23^{rd} May 2018 are considered such that our effective sample size varies over time, as data on younger companies becomes available. The data was retrieved from Datastream and contains adjusted prices for each day from the 31^{st} December 1996 to the 30^{th} April 2018 for a minimum of 39 and a maximum of 320 companies. The risk-free rate is estimated by the German three-months benchmark government bond yields.[7]

In order to derive differences between CS and TS momentum strategies, we apply these and a simple buy-and-hold approach to the data previously introduced. Similarly to Moskowitz et al. (2012), Kim et al. (2016) and Goyal and Jegadeesh (2017), we go long in all stocks during the holding period, which have a return not smaller than a certain threshold in the ranking period, and short the other assets.[8]

The threshold varies with the strategy: CS investments build upon comparisons with

[6]All companies that suffice the Prime Standard are listed in the Prime All Share Index. The Prime Standard is a regulated market segment of the Frankfurt Stock Exchange with high transparency standards (Deutsche Börse Group, 2004).

[7]In order to avoid bias in the estimation of the risk-free rate, it would have been more appropriate to use one-month yields. As these are, however, highly correlated with the three-months yields, we justify the use of the three-months benchmark because of a lack of other data. All returns presented in the following are in excess of the risk-free rate. More information, as summary statistics, concerning our data set can be found in subsection A.1.

[8]We decided against the approach of Jegadeesh and Titman (1993), who go long or short in deciles for their CS portfolio, as there is no comparable decile strategy exploiting only TS momentum, since forming deciles requires cross-sectional comparison. Thus, this method does not comply with the aim of comparing similar strategies. For results concerning decile strategies, please refer to the Appendix of Goyal and Jegadeesh (2017).

the average excess return of all considered stocks in the ranking period, while the TS strategy compares returns in excess of the risk-free rate to zero. Finally, the buy-and-hold strategy roots in going long in any stock exceeding a return of $-\infty$.

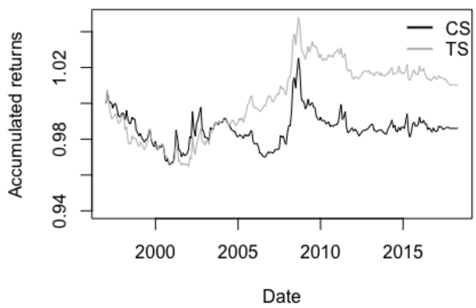
All strategies are repeated for the ranking and holding periods 1, 6 and 12 following the common literature. We disregard longer periods, as Jegadeesh (1990) and De Bondt and Thaler (1985) note return reversals for horizons surpassing one year.[9] Further, we use overlapping portfolios, analogous to Jegadeesh and Titman (1993) and Goyal and Jegadeesh (2017), for holding periods greater than 1 month. We calculate the risk-adjusted alphas in time series regressions according to the Capital Asset Pricing Model (CAPM) and partly to the three-factor model of Fama and French (1993).

The objective of the next section is to analyze which other features, except for the threshold, may influence the returns of momentum portfolios and may thus account for the differences between TS and CS momentum documented by the literature. Hence, we apply ceteris paribus clauses to evaluate the effects of simple changes.

4 Empirical Discussion

Adapting the momentum definitions according to Moskowitz et al. (2012) for a ranking and holding period of 6 months, we obtain the accumulated returns presented in Figure 1. The TS strategy significantly outperforms the CS strategy and ends up with a gain, while the CS strategy closes with a loss. Moskowitz et al. (2012) conclude that the TS momentum surpasses CS momentum. This difference may, however, instead be rooting from special portfolio construction features. In order to

Figure 1: Accumulated returns of the CS and TS strategies with a ranking and holding period of 6 months



[9]We neglect waiting periods between ranking and holding periods, as considered in Korajczyk and Sadka (2004), since our data exhibits no significant short term reversal characteristics, as will be seen in the next section.

assess this hypothesis, we consider portfolios with equal-weighted returns in the first step (initially without net-long positions, before allowing them in the following). In the next step, we weight each asset's return in the portfolios proportional to the inverse of its volatility as introduced by Moskowitz et al. (2012).

4.1 Equal-Weighted Returns

Goyal and Jegadeesh (2017) argue that the CS and TS strategies compared by Moskowitz et al. (2012) differ in terms of the amount of investment on the long and short side of the portfolios. In order to assess the ramifications of positive net-long positions, which are discussed in more detail in Subsection 4.1.2, we initially compare strategies with equally sized long and short sides.

4.1.1 Basic Strategies

In the first step, the long portfolio under each strategy is the equal-weighted portfolio of all stocks with excess returns surpassing the respective threshold during the ranking period and the short portfolio is the equal-weighted portfolio of the remaining stocks. Accordingly, R_t^{strat}, the portfolio's return under the strategy $strat$ with the holding period starting in month t, can be calculated as follows (Goyal and Jegadeesh, 2017):

$$R_t^{strat} = \frac{1}{N^+} \sum_{R_{it-1} \geq th_{strat}} R_{it} - \frac{1}{N^-} \sum_{R_{it-1} < th_{strat}} R_{it},$$

where N^+ and N^- denote the number of long and short positions, R_{it-1} the excess return of the i^{th} stock in the ranking period, R_{it} the excess return of the i^{th} stock in the holding period and th_{strat} the threshold of $strat$. By construction, each strategy invests €0.50 each month on both long and short side of the portfolio.[10] Thus, we declare these strategies as 50/50 strategies in the following. Table 1 reports average returns and alphas for the presented portfolios.[11]

[10] Note that the buy-and-hold portfolio is a pure long position, such that it is not possible to allocate €0.50 to the short position. Therefore, we quit this strategy in this place.

[11] Please refer to Subsection A.2 in the Appendix for details and the complete version of the table containing further measures.

Table 1: Descriptive statistics for 50/50 CS and TS strategies

const	1×1	1×6	1×12	6×1	6×6	6×12	12×1	12×6	12×12
Panel A. Descriptive statistics for 50/50 CS strategies									
Mean	0.0021	0.0177	0.0273	0.0026	0.0198	0.0338	0.0037	0.0137	0.0266
	(0.922)	(3.391)	(3.102)	(1.274)	(3.844)	(3.748)	(1.272)	(2.444)	(2.884)
α_{CAPM}	0.0016	0.0178	0.0288	0.0024	0.0199	0.0325	0.0055	0.0128	0.0258
	(0.707)	(3.483)	(3.266)	(1.166)	(3.871)	(3.578)	(1.89)	(2.393)	(2.763)
Panel B. Descriptive statistics for 50/50 TS strategies									
Mean	-0.0023	-0.0036	0.0183	0.0029	0.012	0.022	0.003	0.0075	0.0181
	(-1.626)	(-1.215)	(0.012)	(1.653)	(3.109)	(3.391)	(1.437)	(1.488)	(2.231)
α_{CAPM}	-0.0017	-0.0037	-0.0366	0.003	0.012	0.0209	0.0044	0.0066	0.017
	(-1.152)	(-1.233)	(-0.035)	(1.659)	(3.115)	(3.197)	(2.145)	(1.388)	(2.079)

Table 1 presents the annualized mean return and alphas obtained in the CAPM (α_{CAPM}) of the 50/50 strategies for the holding and ranking periods 1, 6 and 12. Numbers in parentheses are the corresponding t-statistics. The respective strategy constellation (const) is indicated in the header.

First of all, significantly positive average returns are observed for all 50/50 CS constellations except for those with a holding period of one, which indicates that CS momentum does not hold in the very short term in accordance to the results of Jegadeesh (1990) and De Bondt and Thaler (1985). Howbeit, there is no evidence for short-term mean reversals in contrast to the common literature. The TS strategy only performs significantly positive for the $6\times6, 6\times12$ and 12×12 strategies. Furthermore, its average return falls below that of the CS portfolio for all constellations and is even negative, though not significant, for a ranking period of one month indicating the existence of short-term reversals. Accordingly, the null hypothesis that the average returns of CS and TS portfolios are the same can only be rejected at the 10% level for the constellations with a ranking period of one month.[12] Adjusting for market risk delivers significantly positive alphas exactly for those strategies with significant returns. When additionally taking into account the other Fama and French (1993) factors, the alphas of nearly all strategy constellations increase, whereby, however, most of them lose significance such that only the 6×12 and 12×12 CS strategies

[12]T-statistics for the tests on equality can be found for all strategies in Subsection A.4 in the Appendix.

and the 12×12 TS strategy remain with significant alphas. In magnitude our CAPM alphas fall below those of Moskowitz et al. (2012), who find alphas ranging from 1% to 5%. The median of the CS portfolio is in general higher than the one obtained in the TS portfolio.

However, TS momentum tends to entail a lower standard deviation and skewness, but is marked by a greater kurtosis. Moreover, the Sharpe ratios of the CS constellations surpass their counterparts of the TS strategies except for the 6×1 and 12×1 constellations. As there is also no uniform tendency for the maximum drawdown, no unequivocal statement about the risks of both strategies can be made.

All in all, CS momentum seems to outperform TS momentum, contrary to the results of Moskowitz et al. (2012), although we cannot reject the equality of the returns of CS and TS momentum. One explanation might be that we have ruled out the possibility of net-long positions, which will hence be incorporated in the following.

4.1.2 Time-Varying Net-Long Positions

The TS strategy introduced by Moskowitz et al. (2012) invests \$2 in total without specifying how much is allocated to the long or short side of the portfolio. Therefore, it might happen that the dollar value invested on both sides differs. As the position sizes vary in time, we will refer to these strategies as time-varying (TV) strategies henceforth. Adopting this approach to our definition of returns, we get

$$R_t^{strat} = \frac{1}{N}\Big(\sum_{R_{it-1} \geq th_{strat}} R_{it} - \sum_{R_{it-1} < th_{strat}} R_{it}\Big) \tag{1}$$

with N being the total number of positions held in the portfolio. We test the hypothesis whether this redefinition is the source of TS momentum profits, as maintained by Goyal and Jegadeesh (2017), and report our results in Panel A.1 and Panel B of Table 2.

Comparing the position sizes, we get for a significance level of 0.1% that the TS strategy has a greater long investment than the CS strategy for each single constellation, clearly due to its lower threshold. While we find that the average long position has

Table 2: Statistics for time-varying CS, TS and buy-and-hold strategies

const	1×1	1×6	1×12	6×1	6×6	6×12	12×1	12×6	12×12
Panel A. Statistics for time-varying CS strategies									
Panel A.1. With €Long=€LongCS									
Mean	-0.0014	-0.0078	-0.0157	0.0366	-0.0549	0.0102	0.002	0.0097	0.0103
	(-0.485)	(-1.09)	(-1.512)	(0.08)	(-0.052)	(1.088)	(0.727)	(1.359)	(1.065)
α_{CAPM}	0.0042	-0.0084	-0.0287	0.0043	-0.0018	-0.0025	0.006	0.0074	-0.0366
	(1.96)	(-1.71)	(-4.273)	(1.87)	(-0.377)	(-0.368)	(2.47)	(1.306)	(-0.028)
€ Long	0.1517	0.1538	0.1545	0.3533	0.355	0.3535	0.3974	0.3958	0.3919
Panel A.2. With €Long=€LongTS									
Mean	0.0023	0.0106	0.0197	0.002	0.0107	0.0281	0.003	0.0153	0.016
	(0.997)	(1.783)	(2.116)	(0.776)	(1.754)	(3.064)	(1.096)	(2.127)	(1.64)
α_{CAPM}	0.0037	0.0105	0.0175	0.0045	0.0099	0.0205	0.0058	0.0136	0.0096
	(1.59)	(1.776)	(1.882)	(1.836)	(1.763)	(2.446)	(2.255)	(2.105)	(1.025)
Panel B. Statistics for time-varying TS strategies									
Mean	0.1099	-0.1098	0.0059	0.0019	0.0038	0.0181	0.003	0.0112	0.0099
	(0.287)	(-0.114)	(0.817)	(0.749)	(0.648)	(2.131)	(1.134)	(1.586)	(1.042)
α_{CAPM}	0.0022	-0.1282	0.0037	0.0046	0.0029	0.0107	0.0059	0.0095	0.0033
	(1.101)	(-0.134)	(0.524)	(1.918)	(0.556)	(1.398)	(2.348)	(1.511)	(0.364)
€ Long	0.5133	0.5173	0.5175	0.521	0.5213	0.5185	0.5179	0.5158	0.51
Panel C. Statistics for buy-and-hold strategies									
Mean	0.0663	0.3592	0.2352	0.0831	-0.04	0.2273	0.0301	0.2846	-0.0043
	(0.062)	(0.174)	(0.209)	(-0.081)	(-0.09)	(0.092)	(0.036)	(0.208)	(-0.063)
α_{CAPM}	-0.0041	0.0201	0.0538	-0.0047	0.0195	0.053	-0.0046	0.0194	0.0541
	(-1.71)	(3.948)	(8.319)	(-1.954)	(3.794)	(8.048)	(-1.865)	(3.706)	(8.108)
Panel D. Statistics for TVM strategies									
Panel D.1. As in Goyal and Jegadeesh (2017)									
Mean	0.005	0.0202	0.0314	0.0038	0.0178	0.0373	0.0042	0.0149	0.0224
	(1.742)	(3.414)	(3.18)	(1.258)	(2.63)	(3.164)	(0.974)	(1.525)	(1.695)
α_{CAPM}	0.0057	0.0202	0.0313	0.0057	0.0172	0.0299	0.0083	0.0125	0.0154
	(1.987)	(3.426)	(3.152)	(1.918)	(2.626)	(2.652)	(1.986)	(1.443)	(1.191)
Panel D.2. Adapted on the TS portfolio (TS^{TVM})									
Mean	0.0916	0.0081	0.0171	0.0037	0.0101	0.0217	0.0033	0.0109	0.0192
	(0.293)	(2.018)	(2.576)	(2.301)	(2.527)	(3.227)	(1.663)	(2.592)	(2.67)
α_{CAPM}	0.1099	0.0082	0.0188	0.0038	0.0103	0.0233	0.003	0.0112	0.0227
	(0.364)	(2.063)	(2.84)	(2.292)	(2.631)	(3.461)	(1.453)	(2.699)	(3.214)
Panel D.3. With a total investment in the long and short side of €1									
Mean	0.0067	0.0255	0.0324	0.0048	0.0225	0.0414	0.0048	0.01	0.0185
	(1.688)	(3.433)	(2.523)	(1.212)	(2.381)	(2.405)	(0.738)	(0.743)	(0.966)
α_{CAPM}	0.0074	0.0256	0.0335	0.0063	0.0221	0.0336	0.0103	0.0068	0.0104
	(1.847)	(3.48)	(2.593)	(1.563)	(2.352)	(1.987)	(1.628)	(0.564)	(0.548)

Table 2 presents the annualized mean, alphas obtained from the CAPM model (α_{CAPM}) and the euro amount of the long position in risky assets (€$Long$) for the holding and ranking periods 1, 6 and 12. Numbers in parentheses are the corresponding t-statistics.

increased in value for each TS strategy (though insignificantly), the CS long positions have significantly decreased for all constellations compared to the 50/50 approach. In general, the size of long positions is positively correlated with the ranking period, as average returns of risky assets are more likely to be positive the longer the period of observation is.

With respect to the returns, we unearth that all TV CS constellations underperform their 50/50 counterparts (three of them even significantly). Nevertheless, there is no clear pattern in the change of the corresponding alphas. In contrast, the TS strategies' returns have not changed significantly and there is no tendency observable whether the returns have decreased or increased. Nonetheless, we find that the sign of two alphas changes to the positive, although the magnitude of the alphas still tends to decrease.

Notwithstanding the significantly different sizes of long positions, the returns of the time-varying TS and CS strategy do not significantly differ. However, we observe that the average return of the TS strategies surpasses that of the CS strategies in nearly every constellation. Aiming to counteract the influence of different sized net-long positions, we calculate the returns for the time-varying cross-sectional momentum strategy with the long positions set equal in size to the long positions of the time-varying time-series momentum strategy (CS^{TS}) and report the results in Panel A.2 of Table 2. All returns increase compared to the original TV CS portfolio returns, though only two of them significantly, speaking in favor of the considered hypothesis of Goyal and Jegadeesh (2017). In fact this adjusted time-varying CS portfolio (insignificantly) outperforms the TS portfolio and achieves significantly positive alphas in the CAPM for nearly all constellations. As only the weighting of long and short side was changed, this speaks in favor of higher returns on the long side of the portfolio than on the short side or for the market timing ability of the time-varying TS strategy. The fact that the time-varying TS strategy does not significantly outperform the 50/50 TS strategy speaks in favor of the first reason. Indeed, do the returns of the long side (though insignificantly) surpass the returns of the short side by approximately 0.01. To test for the second hypothetical reason, we regress the size of the net-long positions against the market returns. Results are presented in Table 3.

Table 3: Regression coefficients measuring market timing ability

const	1×1	1×6	1×12	6×1	6×6	6×12	12×1	12×6	12×12
β_{const}	0.0133 (1.952)	0.012 (0.659)	0.0106 (0.423)	0.0041 (0.654)	-0.0071 (-0.430)	0.0046 (0.203)	0.0025 (0.412)	0.0026 (0.158)	-0.0188 (-0.830)

Table 3 presents the slope coefficients β_{const} of the regression according to the model $\bar{R}_t = \alpha + \beta_{const} \cdot NetLong_t^{TS}$ with $\bar{R}_t$ being the cross-sectional equal-weighted average of the holding period returns. Numbers in parentheses are the corresponding t-statistics.

Although we find mainly positive coefficients, none of them is significant at the 5% significance level. Therefore, we argue that the net-long positions are not determined by the market timing ability of the TS strategy.

Contrary to our approach of adjusting the size of the long and short positions, Goyal and Jegadeesh (2017) compare the time-varying TS strategy to the CS^{TVM}. In other words, additionally to the 50/50 CS investments, an investment into the market of the size of the net-long position of the time-varying TS strategy starting in period t ($NetLong_t^{TS}$) is added such that we get a return $R_t^{CS_{TVM}}$ of

$$R_t^{CS_{TVM}} = R_t^{CS} + NetLong_t^{TS} \cdot \bar{R}_t,$$

where $\bar{R}_t$ denotes the return to an equal-weighted position in all assets in the holding period. Panel D.1. of Table 2 presents the results of this strategy. Again, the magnitude of our portfolios' returns falls below the returns reported in the literature (compare the average return of the 1×1 CS^{TVM} strategy of 0.005 in our sample to 0.0285 in the sample of Goyal and Jegadeesh (2017)). Still, similarly to Goyal and Jegadeesh (2017), we find evidence for the CS^{TVM} portfolio surpassing the TV TS portfolio. Subsequently, Goyal and Jegadeesh (2017) conclude that the returns of the TS strategy root from net-long positions and that the CS momentum is indeed superior to the TS momentum. We want to reassess the validity of the comparison of CS^{TVM} and TV TS and the subsequent conclusion.

The returns of the CS^{TVM} and the CS^{TS} portfolio do not significantly differ indicating that the returns of CS^{TVM} can indeed be used in order to adjust for the greater long positions of the TS strategy. Its returns surpass (however, only significantly for the constellations 1×6 and 1×12) those of the time-varying TS portfolio suggesting again that the excess returns of the time-varying TS strategy are rather due to its net-long position than to its threshold. Nonetheless, Goyal and Jegadeesh (2017) forgo adjusting the investment size of the original CS strategy: Imagine a TS portfolio with €0.80 on the long and €0.20 on the short side. The corresponding CS^{TVM} strategy would invest €0.50 on the short side, €0.50 in its long positions and €60 into the market. That is €1.10 in long positions in total. Although its net-long position equals that of the time-varying TS portfolio in value, the total risky investment is significantly greater. This is why we adjust the returns in Panel D.2. of Table 2 to

$$R^{CS}_{TVM} = (1 - NetLong^{TS}_t) \cdot R^{CS}_t + NetLong^{TS}_t \cdot \bar{R}_t.$$

Although the significance of some constellations decreases from the original CS^{TVM} strategy to the standardized alternative, most average returns even increase. The same development can be observed for the alphas of these strategies. This change suggests that the positive returns are not mainly due to the CS strategy returns, but rather to the time-varying investment into the market. The high returns of the buy-and-hold strategy (Panel C of Table 2) speak in favor of this argument. As a consequence of the standardization, only one t-statistic of the test on equality of average returns compared to the TV TS portfolio remains above 2 and one statistic even changes to the negative suggesting that the CS^{TVM} is in fact no "apples-to-apples comparison"[13] measure to the TV TS strategy as maintained by Goyal and Jegadeesh (2017).

Additionally, we report the returns of the TS^{TVM} in Panel D.2. Although the alpha of the CS^{TVM} portfolio beats that of the TS^{TVM} portfolio in nearly all constellations,

[13]See Goyal and Jegadeesh (2017), p. 1795.

we cannot reject the equality of average returns of the strategies. Therefore, we also fail to support the conclusion of Goyal and Jegadeesh (2017) that CS momentum beats TS momentum, if the portfolios are similarly constructed.

When comparing all presented strategies to the buy-and-hold approach, we find that no single constellation succeeds in significantly outperforming buy-and-hold. The buy-and-hold approach does not only surpass the returns of most other portfolios significantly, but even achieves the highest significant CAPM-alphas for all constellations except for those with holding period 1.

To conclude, we find no evidence for a significant change in returns due to pure net-long positions. So this result contradicts the assertion of Goyal and Jegadeesh (2017), who claim that positive returns of the TS strategy result from positive net-long positions. However, our evidence is not exactly comparable to Goyal and Jegadeesh (2017), as the 50/50 CS strategy already outperforms the time-varying TS strategy and we, thus, cannot unequivocally detect the benefits net-long positions of more profitable TS portfolio bear. Notwithstanding the fact that we hence cannot reject the hypothesis that TS momentum returns root from net-long positions, we can assert that the possibility of net-long positions does not unconditionally increase the risk-adjusted returns of positive alpha strategies.

Still, we also fail to bolster Moskowitz et al. (2012) in their evidence of a CS momentum beating TS momentum. Kim et al. (2016) identify volatility weighting, as discussed in the next subsection, as the source of the TS excess returns.

4.2 Volatility Scaling

Moskowitz et al. (2012) argue that the vast difference in volatilities of their assets necessitates scaling the assets' returns, namely equalizing the volatility of each position to 0.4 in order to enable comparisons across asset classes.[14] They estimate the annualized ex-ante volatility σ_{it} by the exponentially weighted lagged squared daily

[14] They justify their choice by the argument that an individual stock's volatility ranges around 0.4, which also holds approximately for our sample (refer to Table 6 in the Appendix).

returns as follows:

$$\sigma_{it-1}^2 = 261 \sum_{s=0}^{\infty} (1-\delta) \cdot \delta^s (R_{it-1-s} - \bar{R}_{it-1})^2. \tag{2}$$

The weights $((1-\delta)\cdot\delta^s)_s$ add up to one and δ is chosen such that the center of mass of the weights is 60[15] and the average return $\bar{R}_{it-1}$ is also calculated as the exponentially weighted average using the same weights. Subsequently, Moskowitz et al. (2012) calculate their TS returns as in equation 1, but with each return R_{it} scaled by its lagged volatility estimate σ_{it-1}:

$$R_t^{scaledRS} = \frac{1}{N} \cdot \left(\sum_{R_{it-1} \geq 0} R_{it} \cdot \frac{40\%}{\sigma_{ti-1}} - \sum_{R_{it-1} < 0} R_{it} \cdot \frac{40\%}{\sigma_{ti-1}} \right).$$

Kim et al. (2016) substantiate that the returns of the scaled TS portfolios are mainly driven by this volatility scaling instead of TS momentum. In order to evaluate this observation, we construct two different portfolios similarly to Asness et al. (2012). The first is unlevered in the sense that the portfolios spend a constant amount, here €0.50, on both long and short sides of the strategies. The second portfolio, implemented as in Moskowitz et al. (2012) and Goyal and Jegadeesh (2017), is scaled such that it invests $\frac{1}{N} \cdot \sum_{i=1}^{N} \frac{0.4}{\sigma_{t-1}}$ in both long and short positions causing the total investment to vary inversely with the ex-ante volatility of the assets[16]. We therefore achieve to differentiate between the effects of the pure volatility weighting and the leveraging[17]. Results of our analysis are presented in Table 4.[18]

First of all, we note that the total investment of the portfolios is significantly larger than €1 for all constellations, when levered. Except for three constellations with

[15]In other words, δ is chosen such that 99.8% of the probability mass is allocated to the 60 days right before time t.

[16]Please refer to Subsection A.3 for further formulas.

[17]As momentum portfolios are net-zero investments, and we thus utilize no equity, the term "leverage" is applied here in an unusual, but related, context compared to literature. We define levered portfolios as those investing more than €1 in risky assets.

[18]As the average returns do not add to the explanatory power of the CAPM alphas in this case, only the latter are analyzed.

Table 4: Statistics for volatility scaled strategies

const	1×1	1×6	1×12	6×1	6×6	6×12	12×1	12×6	12×12
Panel A. Volatility scaled 50/50 CS strategy									
α^u_{CAPM}	-0.0916	0.0097	0.0246	0.0022	0.0176	0.037	0.0078	0.0151	0.0309
	(-0.173)	(1.775)	(2.969)	(1.177)	(3.474)	(4.675)	(3.134)	(3.262)	(3.823)
α^l_{CAPM}	-0.0078	0.0196	0.048	0.0028	0.0268	0.0529	0.0094	0.0387	0.0662
	(-2.321)	(2.136)	(3.651)	(1.084)	(3.52)	(4.822)	(3.138)	(7.199)	(7.655)
Panel B. Volatility scaled time-varying CS strategy with €$Long$=€$LongTS$									
α^u_{CAPM}	0.0029	0.007	0.0094	0.0038	0.0066	0.014	0.0057	0.0107	0.0049
	(1.297)	(1.248)	(1.164)	(1.695)	(1.286)	(1.806)	(2.45)	(1.837)	(0.579)
α^l_{CAPM}	0.2235	0.3044	0.4502	0.1992	0.8325	1.8417	0.2744	1.0515	1.3418
	(1.67)	(0.814)	(0.829)	(1.654)	(2.691)	(4.026)	(2.228)	(3.291)	(2.96)
Panel C. Volatility scaled CS^{TVM} strategy									
α^u_{CAPM}	0.0036	0.0131	0.0265	0.0048	0.0151	0.0338	0.0103	0.0139	0.0196
	(1.078)	(2.337)	(3.095)	(1.898)	(2.413)	(3.602)	(2.805)	(1.864)	(1.832)
α^l_{CAPM}	0.016	0.0369	0.064	0.043	0.0606	0.0824	0.0539	0.0745	0.0952
	(1.561)	(3.267)	(5.049)	(4.166)	(5.284)	(6.442)	(5.117)	(7.425)	(8.662)
Panel D. Volatility scaled 50/50 TS strategy									
α^u_{CAPM}	-0.0022	-0.004	-0.1465	0.0019	0.0091	0.0168	0.0037	0.0054	0.0146
	(-1.794)	(-1.365)	(-0.185)	(1.231)	(2.553)	(2.804)	(2.008)	(1.183)	(1.856)
α^l_{CAPM}	-0.003	-0.0034	0.0059	0.0033	0.0154	0.0302	0.0064	0.0156	0.0322
	(-1.768)	(-0.81)	(0.97)	(1.747)	(3.676)	(4.505)	(3.118)	(3.036)	(3.914)
Panel E. Volatility scaled time-varying TS strategy									
α^u_{CAPM}	0.0018	-0.0183	0.0027	0.0035	0.0013	0.0072	0.0055	0.0072	0.1282
	(0.946)	(-0.019)	(0.41)	(1.586)	(0.262)	(0.99)	(2.378)	(1.258)	(0.078)
€$Long^u$	0.5119	0.5158	0.5162	0.5214	0.5217	0.5195	0.5185	0.5169	0.5112
α^l_{CAPM}	0.0033	0.0027	0.0138	0.0048	0.0088	0.0303	0.0076	0.0219	0.0251
	(1.28)	(0.385)	(1.419)	(1.663)	(1.28)	(3.028)	(2.543)	(2.797)	(2.227)
€$Long^l$	0.8144	0.8176	0.8106	0.8617	0.858	0.8461	0.8747	0.8673	0.848
€$Total$	1.5298	1.52	1.5034	1.5281	1.518	1.501	1.5327	1.5224	1.5052
Panel F. Volatility scaled buy-and-hold strategy									
α^u_{CAPM}	-0.0044	0.0164	0.0486	-0.005	0.0153	0.0476	-0.0047	0.0153	0.048
	(-1.837)	(3.164)	(7.663)	(-2.081)	(2.941)	(7.366)	(-1.953)	(2.884)	(7.296)
α^l_{CAPM}	-0.0041	0.0201	0.0538	-0.0047	0.0195	0.053	-0.0046	0.0194	0.0541
	(-1.71)	(3.948)	(8.319)	(-1.954)	(3.794)	(8.048)	(-1.865)	(3.706)	(8.108)

Table 4 presents the annualized alphas obtained from the CAPM model (α^u_{CAPM} for the respective unlevered strategy, α^l_{CAPM} for the respective levered strategy) and the euro amount of the long position in risky assets (€$Long^u$ for the respective unlevered strategy, €$Long^l$ for the respective levered strategy) for the holding and ranking periods 1, 6 and 12. Numbers in parentheses are the corresponding t-statistics.

ranking period 1, all levered strategies outperform their unlevered counterparts on average. The t-statistics comparing those strategies tend to increase with the holding period suggesting that leverage by the sum of the inverse volatilities (referred to as volatility leveraging in the following) has positive effects in the long term. For instance, four of the seven t-statistics[19] are significant at the 5% level for 12×12 strategies. As time-invariant leverage of portfolios does not change the signs of alphas, nor influences the value of t-statistics, we can state that volatility leveraging beats simple leveraging, since nearly all t-statistics increased and the sign switches for two constellations (50/50 TS 1×12, time-varying TS 1×6). The alpha of one CS strategy (the 12×12 volatility scaled time-varying CS strategy with $€Long{=}€LongTS$) pertains even a value of 1.34.[20]

In order to evaluate the effects of the pure volatility weighting, we will consider only the unlevered alphas in the following. The long positions of the time-varying TS strategy have not changed significantly from the case without volatility scaling allowing unbiased comparisons between scaled and unscaled strategies. Comparing with the 50/50 portfolios, no significant changes in alphas can be observed. However, surprisingly more alphas have fallen than risen, when changing the weights of the assets in the portfolios. Even when comparing the alphas of the other scaled strategies with their unscaled counterpart, we obtain insignificant, but negative t-statistics indicating that the pure change in weighting renders deteriorated returns. Further, many alphas lose significance. Compare, for instance, the three significant alphas for the CS^{TS} strategy with the sole significant alpha for its scaled alternative. This observation may be due to the lack of low-risk assets, like corporate bonds, in our sample.[21]

Comparisons across the volatility scaled portfolio strategies deliver that the buy-and-hold approach surpasses all other strategies for holding periods greater than one

[19] Please refer to Table 8 in the Appendix.

[20] Indeed, we find significant alphas for TS and CS portfolios, where the assets are equally-weighted, but the monthly investment in long and short side fluctuates with the mean of the inverse volatility of all stocks included. Please refer to Table 10 for more details.

[21] Please refer to Subsection 4.4 for further details.

Table 5: Average monthly turnover of portfolio strategies

const	1×1	1×6	1×12	6×1	6×6	6×12	12×1	12×6	12×12
50/50 CS	1.0338	1.0372	1.0365	0.611	0.6118	0.6157	0.4474	0.449	0.4452
scaled 50/50 CS	1.1604	1.1485	1.1317	1.12	1.1157	1.1174	0.8919	0.887	0.8714
CS^{TVM}	1.2991	1.3042	1.3053	0.7263	0.7278	0.7321	0.5291	0.5301	0.5256
scaled CS^{TVM}	1.5604	1.5484	1.5283	1.3118	1.3075	1.3071	1.041	1.0334	1.016
time-varying TS	0.9922	0.9946	0.9963	0.3556	0.3549	0.3556	0.2479	0.2471	0.2449
scaled time-varying TS	1.6818	1.6755	1.6616	0.8285	0.8226	0.8144	0.6856	0.6798	0.668
scaled BAH	0.3374	0.3368	0.3345	0.3371	0.3365	0.3342	0.3343	0.3336	0.3311

Table 5 presents the average monthly turnover of each introduced strategy for the holding and ranking periods 1, 6 and 12. Scaled strategies refer to the levered scaled strategy as introduced by Moskowitz et al. (2012) and Goyal and Jegadeesh (2017).

month (in contrast to the evidence of short term mean reversion by Jegadeesh and Titman (1993)) and that the CS^{TVM} performs best in exactly these excluded constellations. The scaled 50/50 as well as TV TS strategy render the lowest alphas going along with the findings of Goyal and Jegadeesh (2017) and Kim et al. (2016).

To conclude, we support Kim et al. (2016) and Goyal and Jegadeesh (2017) in their observation that TS momentum fails to surpass CS momentum, when both portfolios' assets are weighted inversely to their volatility. However, we find that it is not the pure weighting that explains the significant rise in returns, but the leveraging.

4.3 Turnover

An important factor influencing the profitability of investments is the height of transaction costs. As those differ across markets, we compare the turnover of the different strategies instead.[22] The turnover is calculated similarly to Goyal and Jegadeesh (2017) as the sum of the absolute changes in the portfolio weights for both long and short side. Results are presented in Table 5.[23]

[22]As this analysis only touches the surface of the transaction costs problem, Goyal and Jegadeesh (2017) refer to Novy-Marx and Velikov (2015) for further arguments to the topic and undermine the importance of the findings on turnover numbers.

[23]As the buy-and-hold approach has per definition no turnover, results for this strategy are omitted. Further, only those strategies analyzed by Goyal and Jegadeesh (2017) are compared.

In general, we observe that the turnover decreases strongly with the ranking period (compare a turnover of 1.03 for the 1×1 and 0.45 for the 12×1 $50/50$ CS strategy) and slightly with the holding period.[24] The levered scaled strategies' turnover obviously surpasses those of the unlevered strategies, even significantly for nearly every constellation. The scaled buy-and-hold (BAH) portfolio is marked by the lowest turnover, and thus transaction costs, of the presented strategies. Still, there is no significant difference between the TS strategy and the buy-and-hold approach for those constellations with a ranking period of 6 months. For ranking periods of 12 months the TV TS strategies' turnover even falls under the turnover of the BAH portfolio.
Similarly to Goyal and Jegadeesh (2017), we find that the turnover for CS strategies surpasses that of TS strategies significantly for ranking periods greater 1 month. CS^{TVM} is marked by the highest average turnover. Although its turnover is around 0.1 smaller than the turnover of the scaled time-varying strategy for constellations with a ranking period of one month, this pattern reverses for other constellations. Nonetheless, those strategies with time-varying long investment amounts tend to require more sales and purchases.
All in all, we notice that those strategies with higher returns trend towards higher turnover rates. In order to exclude the possibility that the higher returns serve to compensate for higher transaction costs, we regress the difference in returns of two strategies on the difference in turnover numbers.[25] However, there is no significant positive relationship observable for any combination of strategy turnovers. Therefore, we conclude that turnover does not explain higher returns.

4.4 Restrictions to the Empirical Analysis

Our analysis underlies several restrictions, which exacerbate comparing it to other papers. To start with, parameters for e.g. ranking and holding periods were not

[24]The validity of this statement suffers under the strong correlation of asset selection caused by overlapping portfolios.

[25]Please refer to Subsection A.5 in the Appendix for further details

chosen congruently to the literature. Compared to Moskowitz et al. (2012), who include periods 1, 3, 6, 9, 12, 24, 36, and 48, we restrict the analysis to 3 distinct periods. As Goyal and Wahal (2015) state "momentum portfolios formed from 12 to 7 months prior to the current month deliver higher future returns than momentum portfolios formed from 6 to 2 months prior"[26], our restrictions may lead to lower returns than found in the common literature.

To continue with, due to wanting data access our effective sample size varies over time such that interpretations suffer under sample bias. On the one hand, the data of 1996 is thus not representative for the Prime All Share Index of that time as the sampling method induces survivorship bias. On the other hand do the sample characteristics change over time influencing momentum profits.

Further, we report significant alphas for buy-and-hold strategies in Panel C of Table 2. Assuming the CAPM holds true, this indicates that our sample outperforms the market portfolio and is thus not representative for the market. As we only include stocks, which suffice the high standards of Frankfurt's stock market, taking into consideration General Standard stocks might change the results.

Moreover, although Moskowitz et al. (2012) document momentum returns for liquid future markets and additionally show the independence of their results to diverse liquidity measures, other papers, e.g. Lesmond et al. (2004), document momentum in the least liquid stocks. This latter result could account for the mass of insignificant alphas in our sample.

Further, we only consider individual stocks[27]. Moskowitz et al. (2012), however, note significant returns to TS momentum for future contracts. Menkhoff et al. (2012) list various sources of risks of future contracts not captured in the traditional three-factor model of Fama and French (1993), such that Kim et al. (2016) find significant alphas even for the buy-and-hold strategy applied on future contracts. To evade the

[26]See Goyal and Wahal (2015), p. 1237.

[27]We even take into account preference stocks, which are, for example, excluded by Goyal and Jegadeesh (2017).

risk influences, we restrict our analysis to the German stock market.

What is more, not only do we consider a different market than most other studies, but also a different time period. Goyal and Jegadeesh (2017), for example, report results for 1946 to 2013, such that their data set starts half a century before ours. For instance, Barroso and Santa-Clara (2015) and Baltas and Kosowski (2017) find no evidence of momentum returns in recent decades, which is partly due to its discovery and exploitation by investment funds as well as the recent financial crisis. As our sample starts in the late 90s, it is no surprise that we observe no significant returns for the different momentum strategies. An in time extended analysis of the different strategies might therefore lead to new insights.

Last but not least, Kim et al. (2016) ascertain risk parity as the source of positive TS momentum returns. Asness et al. (2012) argue that the abnormal returns in risk parity result from the difference in risk of the assets. Thus, risk parity performs well in data sets with a great cross-sectional variation of volatility. While the portfolio of Moskowitz et al. (2012) has an average annualized volatility of only 0.1964 with a standard deviation of 0.1156, our sample's volatility only exhibits a standard deviation of 0.0435 and reaches an average of 0.3167. Therefore, the portfolio of Moskowitz et al. (2012) is more diversified with lower total risk and profits accordingly more from volatility scaling than our sample. High returns are especially due to the inclusion of bonds (Asness et al., 2012). In our more diversified sample, where 65 bond indices were included, we achieve a similar ratio of bonds to other assets as Moskowitz et al. (2012).[28] Indeed, our results (as presented in Table 11 in the Appendix) indicate that nearly all strategies, conducted on the new sample, exhibit significant changes to positive alphas compared to the original sample.

[28]Moskowitz et al. (2012) include 13 bonds in their sample of 55 assets, while we include 65 bond indices in our sample of 385 assets.

5 Conclusion

Our central aim is to examine the differences between CS and TS momentum for stocks included in the Prime All Share Index. Building upon Kim et al. (2016), Goyal and Jegadeesh (2017) and Moskowitz et al. (2012), we go long on assets which exceed a strategy specific threshold, and short the other assets. A first comparison between CS and TS strategies confirms our hypothesis of the TS strategy outperforming the CS strategy. However, when comparing the strategies with equally-sized long and short sides, the results are mixed, although there exists a tendency for the CS strategy to outperform the TS strategy. After allowing for net-long positions, CS strategies seem to achieve smaller returns, but there establishes no clear pattern. The increased returns of the TS portfolio support the results of Goyal and Jegadeesh (2017), although nearly all increases are insignificant. When using the same method as Goyal and Jegadeesh (2017) by constructing a CS^{TVM} portfolio, we do not find a significant difference in returns compared to our 50/50 approach. The CS portfolio still outperforms the TS portfolio, speaking in favor of the arguments of Goyal and Jegadeesh (2017). Regarding volatility scaling, we follow Asness et al. (2012) and construct portfolios, where the position sizes vary anti-proportionally to the assets' volatility. We observe that the change in weightings does not entail effects as strong as those of the change in investment sizes by the scaling. Howbeit the significant increases in return, the turnover, and thus the transaction costs, increase with the scaling.

Apart from all that, we note that the buy-and-hold strategy outperforms nearly every other strategy bolstering that we cannot predict future prices by past returns only. Hence, momentum does not challenge the random walk hypothesis in our sample.

Future research could examine which other anomalies, except for momentum, can be amplified by volatility scaling and scrutinize underlying behavioral theories, building upon the theory of leverage aversion, introduced by Asness et al. (2012) in order to unearth new evidence battling the random walk hypothesis.

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A Appendix

A.1 Summary Statistics of the Sample

Panel A of table 6 summarizes the date of the first reported return in our sample (Start Date), the average annualized return and average volatility (estimated by equation 2) for every single company listed in the Prime All Share Index on the 2^{nd} of May. We omit some companies of that index because of data too small for estimating the volatility consistently. Panel B continues to list the bond indices included in the more diversified sample. We merge our original data set with daily data on 65 different bond indices traded on the Frankfurt Stock Exchange in order to obtain a more diversified sample for Subsection 4.4.

Table 6: Summary statistics for all assets in the analyzed sample

Nr.	Name according to Datastream	Start Date	Return	Volatility
Panel A. Stocks				
1	SAP	1996-12-18	0.16	0.3155
2	SIEMENS	1996-12-18	0.10	0.3025
3	BAYER	1996-12-18	0.08	0.2864
4	ALLIANZ	1996-12-18	0.05	0.3042
5	BASF	1996-12-18	0.09	0.2664
6	DAIMLER	1996-12-18	0.02	0.3038
7	DEUTSCHE.TELEKOM	1998-10-27	0.02	0.2919
8	BMW	1996-12-18	0.11	0.308
9	VOLKSWAGEN	1996-12-18	0.17	0.363
10	CONTINENTAL	1996-12-18	0.18	0.3374
11	ADIDAS	1996-12-18	0.14	0.2865
12	DEUTSCHE.POST	1996-12-18	0.04	0.2599
13	SIEMENS HEALTHINEERS	omitted		
14	FRESENIUS	2018-03-16	0.12	0.2798
15	MUENCHENER.RUCK.	1999-03-24	0.06	0.2818
16	FRESENIUS.MED.CARE	1996-12-18	0.07	0.2599
17	INFINEON.TECHS.	1996-12-18	0.04	0.431
18	BEIERSDORF	2000-03-13	0.11	0.2629
19	DEUTSCHE.BANK	1996-12-18	0.01	0.3517
20	HENKEL	1996-12-18	0.09	0.2467
21	DEUTSCHE.BOERSE	1997-12-01	0.13	0.2859
22	E.ON.N	2001-02-02	0.00	0.28
23	INNOGY	1996-12-18	0.01	0.209
24	VONOVIA	2016-10-07	0.20	0.2017
25	COVESTRO	2013-07-10	0.49	0.273
26	HEIDELBERGCEMENT	2015-10-06	0.10	0.3388
27	WIRECARD	1996-12-18	0.57	0.5958
28	EVONIK.INDUSTRIES	2000-10-24	-0.03	0.2091
29	THYSSENKRUPP	2013-04-25	0.06	0.336
30	DEUTSCHE.WOHNEN BR.SHS.	1996-12-18	0.08	0.3365
31	HANNOVER.RUCK.	2006-03-27	0.13	0.2863
32	X1.1.DRILLISCH	1997-01-24	0.27	0.5008
33	COMMERZBANK	1998-10-12	-0.04	0.3788
34	DEUTSCHE.LUFTHANSA	1996-12-18	0.07	0.3216
35	MERCK.KGAA	1996-12-18	0.10	0.2861
36	RWE	1996-12-18	-0.00	0.289

37	TELEFONICA.DTL. HLDG.	1996-12-18	-0.02	0.2321
38	UNITED.INTERNET	2012-10-29	0.30	0.4285
39	ZALANDO	1998-10-12	0.24	0.341
40	HOCHTIEF	2014-09-30	0.13	0.373
41	UNIPER.SE	1996-12-18	0.71	0.2386
42	DELIVERY.HERO	2016-09-12	0.53	0.3113
43	KION.GROUP	2017-06-30	0.24	0.2574
44	MTU.AERO.ENGINES HLDG.	2013-06-27	0.18	0.3022
45	SYMRISE	2005-06-03	0.14	0.2686
46	TALANX.AKTGSF.	2006-12-08	0.11	0.1943
47	WACKER.CHEMIE	2012-10-01	0.10	0.3908
48	AXEL.SPRINGER	2006-04-10	0.07	0.2576
49	BRENNTAG	1998-11-11	0.13	0.2247
50	DWS.GROUP	omitted		
51	FRAPORT	2018-03-23	0.06	0.2681
52	HELLA.GMBH...KGAA	2001-06-08	0.21	0.2771
53	PUMA	2014-11-11	0.16	0.3169
54	QIAGEN	1996-12-18	0.12	0.3471
55	BOSS..HUGO.	1998-05-04	0.16	0.3539
56	FIELMANN	1999-04-23	0.12	0.2516
57	GEA.GROUP	1996-12-18	0.07	0.3359
58	HAPAG.LLOYD	1996-12-18	0.30	0.3482
59	LANXESS	2015-11-06	0.15	0.3355
60	LEG.IMMOBILIEN	2005-01-31	0.14	0.1944
61	OSRAM.LICHT	2013-01-31	0.18	0.3081
62	PROSIEBENSAT.1 MEDIA	2013-07-05	0.15	0.439
63	RATIONAL	1997-07-07	0.22	0.3179
64	AURUBIS	2000-03-03	0.13	0.3069
65	BECHTLE	1998-10-16	0.14	0.3396
66	CARL.ZEISS.MEDITEC	2000-03-29	0.12	0.3598
67	CECONOMY	2000-03-22	0.03	0.3082
68	CTS.EVENTIM	1996-12-18	0.28	0.4489
69	DMG.MORI	2000-02-01	0.84	0.5929
70	DUERR	1998-11-18	0.12	0.3245
71	FREENET	1996-12-18	0.13	0.4418
72	FUCHS.PETROLUB	1999-12-06	0.20	0.2739
73	GRENKE.N	1999-01-08	0.21	0.3383
74	K...S	2000-04-03	0.16	0.3277
75	KRONES	1998-09-29	0.17	0.3217
76	KUKA	1998-10-23	0.12	0.3423
77	METRO	1996-12-18	-0.38	0.2146
78	MORPHOSYS	2017-07-13	0.33	0.5529
79	NEMETSCHEK	1999-03-17	0.23	0.4668
80	RHEINMETALL	1999-03-11	0.17	0.3594
81	ROCKET.INTERNET	1996-12-18	-0.03	0.4641
82	SALZGITTER	2014-10-02	0.14	0.3568
83	SARTORIUS	1998-10-12	0.33	0.4243
84	SCHAEFFLER	1999-05-05	0.01	0.2993
85	SCOUT24	2015-10-09	0.17	0.2653
86	SILTRONIC	2015-10-01	0.70	0.4219
87	SIXT	2015-06-11	0.15	0.3965
88	SOFTWARE	1998-03-23	0.16	0.4148
89	STADA.ARZNEIMITTEL	1999-04-27	0.15	0.3077
90	STROEER	1998-10-21	0.19	0.3546
91	SUEDZUCKER	2010-07-14	0.01	0.2754
92	AAREAL.BANK	1998-10-29	0.14	0.392
93	ADO.PROPERTIES	2002-06-18	0.34	0.2426
94	AIXTRON	2015-07-23	0.16	0.5363
95	ALSTRIA.OFFICE.REIT	1998-10-12	0.02	0.3174
96	BILFINGER.BERGER	2007-04-02	0.06	0.3478
97	CANCOM	1996-12-18	0.27	0.4607
98	COMDIRECT.BANK	1999-09-17	0.00	0.3349
99	COMPUGROUP.MEDICAL	2000-06-02	0.10	0.2778
100	DEUTSCHE.EUROSHOP	2000-07-11	0.02	0.1982

101	DIEBOLD.NIXDORF	2000-12-29	0.10	0.2922
102	DT.PFANDBRIEFBANK	2004-05-19	0.09	0.2734
103	EVOTEC	2015-07-15	0.16	0.5375
104	GERRESHEIMER	1999-11-11	0.06	0.2727
105	HAMBURGER.HAFEN.UND.LOGISTIK	2007-06-08	-0.06	0.3112
106	HELLOFRESH	2007-11-01	0.30	0.3814
107	JENOPTIK	2017-11-01	0.08	0.3726
108	JUNGHEINRICH.PFS.	1998-10-12	0.15	0.331
109	KWS.SAAT	1996-12-18	0.11	0.2393
110	LEONI	2000-05-29	0.14	0.3604
111	MVV.ENERGIE	1998-11-27	0.02	0.2117
112	NORMA.GROUP	1999-06-01	0.17	0.2905
113	PATRIZIA.IMMOBILIEN	2011-04-07	0.13	0.4298
114	RHOEN.KLINIKUM	2006-03-30	0.10	0.2898
115	SMA.SOLAR.TECH.	1998-10-19	0.15	0.5474
116	STABILUS	2008-06-26	0.36	0.3116
117	TAG.IMMOBILIEN	2014-05-22	0.02	0.3247
118	TLG.IMMOBILIEN	2000-11-27	0.23	0.2033
119	VTG	2014-10-24	0.12	0.312
120	WACKER.NEUSON	2007-06-27	0.07	0.3879
121	WUESTENROT...WUERTT	2007-05-14	-0.03	0.2571
122	XING	1999-09-13	0.26	0.3651
123	ACCENTRO.RLST.	2006-12-06	0.01	0.4536
124	ADLER.REAL.ESTATE	2007-03-30	0.39	0.4501
125	ADVA.OPTICAL.NETWG	2003-05-30	0.23	0.6346
126	ALL.FOR.ONE.STEEB	1999-03-30	0.15	0.4487
127	ALZCHEM	1998-12-01	-0.54	0.7452
128	AMADEUS.FIRE	2017-10-05	0.19	0.3981
129	ATOSS.SOFTWARE	1999-03-30	0.15	0.4113
130	AUMANN	2000-03-21	0.05	0.3812
131	BASLER	2017-03-24	0.15	0.4733
132	BAUER	1999-03-24	0.11	0.3974
133	BAYWA	2006-07-03	0.11	0.263
134	BEFESA	2001-12-28	0.94	0.2603
135	BERTRANDT	2017-11-02	0.15	0.3532
136	BET.AT.HOME.COM	1998-10-12	0.28	0.4516
137	BIOFRONTERA	2005-12-23	0.09	0.5233
138	BIOTEST	2006-10-30	0.17	0.3828
139	BORUSSIA.DORTMUND	1999-06-18	0.01	0.3522
140	BRAIN.BIOTECHNOLOGY	2000-10-30	0.48	0.417
141	CENTROTEC.SUST.	2016-03-14	0.13	0.4076
142	CEWE.COLOR.HOLDING	1998-12-15	0.12	0.3167
143	CORESTATE.CAPITAL HLDG.	1998-10-12	0.82	0.2469
144	CROPENERGIES	2016-10-04	0.02	0.3913
145	DATA.MODUL	2006-09-28	0.14	0.4237
146	DEMIRE.REAL.ESTATE	1998-10-19	0.06	0.525
147	DERMAPHARM.HOLDING	2006-07-25	0.29	0.0959
148	DEUTSCHE.BET.	2018-02-09	0.05	0.3131
149	DEUTZ	1998-10-28	0.13	0.4329
150	DIALOG.SEMICON.	1996-12-18	0.25	0.6065
151	DIC.ASSET	1999-10-14	0.01	0.3726
152	DR.HOENLE	2006-04-13	0.18	0.3938
153	DRAEGERWERK.PREF.	2001-01-23	0.12	0.3478
154	DT.KONSUM.REIT	1998-11-02	0.54	0.314
155	EDAG.ENGINEERING GP.	2015-12-15	-0.10	0.2847
156	ELMOS.SEMICON.	2015-12-02	0.12	0.4588
157	ELRINGKLINGER.N	1999-10-12	0.17	0.35
158	ENCAVIS	2002-06-17	0.34	0.6288
159	FIRST.SENSOR	1998-10-16	0.13	0.4595
160	GERRY.WEBER.INTL.	1999-07-16	0.09	0.3493
161	GESCO	1999-03-05	0.09	0.2707
162	GFT.TECHNOLOGIES	1998-11-11	0.15	0.5328
163	GK.SOFTWARE	1999-06-29	0.22	0.342
164	GODEWIND.IMMOBILIEN	omitted		

165	GRAMMER	2018-04-05	0.10	0.36
166	H...R	1998-11-04	0.11	0.3386
167	HAMBORNER.REIT	2000-06-12	0.01	0.1983
168	HAWESKO.HOLDING	2000-10-12	0.05	0.2657
169	HEIDELBERGER DRUCKMASCHINEN	1999-01-20	-0.05	0.3947
170	HIGHLIGHT.COMMS.	1998-03-16	0.08	0.3995
171	HORNBACH.HOLDING	1999-05-12	0.06	0.2686
172	HORNBACH.BAUMARKT	1996-12-18	0.03	0.2686
173	HYPOPORT.FINANCE	1998-11-09	0.31	0.3934
174	INDUS.HOLDING	2007-10-26	0.04	0.2685
175	INSTONE.REAL.ESTATE.GROUP	1998-11-09	-0.24	0.0939
176	ISRA.VISION	2018-02-15	0.10	0.368
177	JOST.WERKE	2000-04-20	0.32	0.2696
178	KLOECKNER...CO	2017-07-20	0.07	0.4228
179	KOENIG...BAUER	2006-06-27	0.12	0.3648
180	KPS	1999-09-24	0.36	0.7729
181	LEIFHEIT	1999-07-15	0.04	0.3065
182	LOGWIN	1999-06-18	0.09	0.4953
183	LOTTO24	2000-03-20	0.32	0.3707
184	MANZ	2012-07-02	0.22	0.5503
185	MAX.AUTOMATION	2006-09-21	0.08	0.3978
186	MBB	1999-05-07	0.27	0.3945
187	MEDICLIN	2006-05-08	0.01	0.3502
188	MEDIGENE	2000-12-05	0.06	0.5988
189	MLP	2000-06-29	-0.02	0.3856
190	NEXUS	1998-10-15	0.14	0.4285
191	NORDEX	2000-07-21	0.02	0.5383
192	OHB	2001-03-30	0.15	0.3978
193	OVB.HOLDING	2001-03-12	0.00	0.2687
194	PARAGON	2006-07-20	0.26	0.4776
195	PFEIFFER.VACUUM TECH.	2000-11-28	0.11	0.3319
196	PROCREDIT.HOLDING	1998-10-12	-0.07	0.2936
197	PSI.SOFTWARE	2016-12-23	0.06	0.4655
198	PVA.TEPLA	1998-10-12	0.19	0.5756
199	RIB.SOFTWARE	1999-06-22	0.19	0.3726
200	S.T	2011-02-08	0.12	0.502
201	SAF.HOLLAND	2000-11-17	0.21	0.5108
202	SCHALTBAU.HOLDING	2007-07-25	0.12	0.3615
203	SECUNET.SCTY.NET.	1999-01-27	0.26	0.5209
204	SENVION	1999-11-10	-0.15	0.2818
205	SERVICEWARE	omitted		
206	SGL.CARBON	2018-04-20	0.01	0.4314
207	SHOP.APOTHEK.EUROPE	1996-12-18	0.31	0.3869
208	SIXT.LEASING	2016-10-13	-0.03	0.2722
209	SLM.SOLUTION.GROUP	2015-05-07	0.22	0.3625
210	STRATEC.BIOMEDICAL	2014-05-08	0.26	0.4273
211	SUESS.MICROTEC	2000-09-21	0.17	0.5512
212	SURTECO	1999-05-19	0.02	0.2838
213	TAKKT	1999-10-20	0.09	0.3383
214	TECHNOTRANS	1999-09-15	0.14	0.4213
215	TELE.COLUMBUS	1998-10-12	-0.08	0.2612
216	TOM.TAILOR.HOLDING	2015-04-14	0.01	0.3741
217	USU.SOFTWARE	2010-03-25	-0.01	0.3873
218	VAPIANO	2000-03-21	-0.00	0.2541
219	VARTA	2017-06-27	0.16	0.2388
220	VERBIO.VER. BIOENERGIE	2017-10-19	0.07	0.5993
221	VILLEROY...BOCH	2006-10-13	0.07	0.3225
222	VISCOM	1998-11-18	0.07	0.3766
223	VOLTABOX	2006-05-09	-0.46	0.4181
224	VOSSLOH	2017-10-13	0.06	0.3125
225	WASHTEC	1997-08-18	0.22	0.4176
226	ZEAL.NETWORK	1998-11-02	0.08	0.3831
227	ZOOPLUS	2005-10-11	0.34	0.3667
228	X11.88.0.SOLUTIONS	2008-05-08	-0.01	0.5184

229	X3U.HOLDING	1999-04-23	0.02	0.4765
230	X4.SC	1999-11-26	0.04	0.5252
231	A.S.CREATION	2005-12-15	0.04	0.2916
232	AAP.IMPLANTATE	1999-02-24	0.11	0.5971
233	AD.PEPPER.MEDIA INTL.	1999-05-11	0.10	0.552
234	ADLER.MODEMARKTE	2000-10-06	-0.07	0.3222
235	AHLERS	2011-06-21	-0.03	0.3178
236	ARTNET	1996-12-18	0.26	0.7979
237	BASTEI.LUEBBE	1999-05-19	-0.17	0.2687
238	CENIT	2013-10-08	0.13	0.4356
239	CONSTANTIN.MEDIEN	1998-10-12	0.01	0.521
240	DEAG.DEUTSCHE.ENTM	1998-10-12	0.07	0.5283
241	DELTICOM	1998-10-12	0.03	0.3637
242	ECKERT...ZIEGLER	2006-10-25	0.11	0.4085
243	ECOTEL.COMM.	1999-05-31	0.05	0.4289
244	EINHELL.GERMANY	2006-03-28	0.16	0.3231
245	ELUMEO	1998-10-22	-0.28	0.4256
246	EPIGENOMICS.N	2015-07-03	0.06	0.6205
247	ERMN.COMM...CNTL. TECH.	2004-07-19	-0.00	0.3727
248	FABASOFT	1998-10-13	0.19	0.5085
249	FORTEC.ELEKTRONIK	1999-10-04	0.10	0.3564
250	FRANCOTYP.POSTALIA HLDG.	1999-02-18	-0.05	0.4356
251	GERATHERM.MEDICAL	2006-11-29	0.05	0.3322
252	GIGASET	omitted		
253	HEIDELBERG.PHARMA	2002-02-07	-0.03	0.5886
254	HOLIDAY.CHECK.GROUP	2006-11-10	0.01	0.4638
255	INIT	2000-07-12	0.15	0.3851
256	INTERSHOP.COMMS.	2001-07-23	0.07	0.6392
257	INTICA.SYSTEMS	1998-10-12	0.11	0.4702
258	INVISION.SOFTWARE	2004-11-08	0.07	0.44
259	IVU.TRAFFIC.TECHS.	2007-06-15	0.21	0.6374
260	KROMI.LOGISTIK	2000-07-06	-0.03	0.3235
261	LPKF.LASER...ELTN.	2007-03-07	0.18	0.546
262	LUDWIG.BECK	1998-12-01	0.06	0.2924
263	MASTERFLEX	1999-06-17	0.01	0.374
264	MEVIS.MEDICAL.SLTN	2000-06-15	0.07	0.4437
265	MOLOGEN	2007-11-15	0.14	0.5729
266	MYBET.HOLDING	2001-11-06	0.05	0.732
267	NFON	omitted		
268	PAION	1996-12-18	0.18	0.6275
269	PHOENIX.SOLAR	2005-02-11	0.02	0.6828
270	PNE.WIND	2004-11-19	0.06	0.5336
271	PROGRESS.WERK OBERKIRCH	1998-12-16	0.06	0.261
272	QSC	1999-08-05	0.01	0.5179
273	R.STAHL	2000-04-19	0.05	0.3012
274	SFC.ENERGY	1998-11-02	0.04	0.4931
275	SINGULUS.TECHS.	2006-04-21	-0.06	0.5812
276	SINNERSCHRADER	1998-05-04	0.08	0.4534
277	SKW.STAHL.METGIE. HLDG.	1999-11-03	-0.11	0.5238
278	SLEEPZ	2006-11-30	0.22	0.7176
279	SMT.SCHARF	1999-07-05	0.07	0.2979
280	SNP.SCHNNEUR...PTN	2007-04-10	0.37	0.4388
281	SOFTING	2001-06-04	0.10	0.4711
282	SYGNIS	2000-05-15	-0.11	0.6463
283	SYZYGY	2000-08-10	0.04	0.3532
284	TELES	2000-10-05	0.23	0.8437
285	UMS.UTD.MED.SYS.INTL.	1998-10-12	0.03	0.58
286	UNITED.LABELS	2000-07-14	0.14	0.6522
287	VA.Q.TEC	2000-05-09	0.17	0.3397
288	VITA.34.INTL.	2016-09-30	0.11	0.4622
289	WESTAG...GETALIT	2007-03-26	0.04	0.2704
290	WINDELN	2000-01-03	-0.45	0.4255
291	YOC	2015-05-06	0.09	0.5554
292	ZHONGDE.WASTE.TECH	2006-06-01	-0.10	0.6086

293	AIRBUS	2007-07-05	0.14	0.3451
294	AROUNDTOWN	2000-07-12	0.20	0.2323
295	BB.BIOTECH	2015-11-26	0.08	0.2733
296	BUWOG	2000-06-12	0.19	0.2033
297	C.QUADRAT.INV...FRA.	2014-04-28	0.08	0.3894
298	DIEBOLD	2006-03-29	-0.27	0.3576
299	EXCEET.GROUP	2016-08-12	-0.04	0.2987
300	FERRATUM	2010-02-04	0.17	0.3757
301	FYBER.N	2015-02-06	-0.34	0.7263
302	GRAND.CITY.PROPS.	2015-08-13	0.28	0.2379
303	PETRO.WELT.TECHS.	2013-01-10	0.02	0.4455
304	RTL.GROUP	2006-05-03	0.02	0.2358
305	STEINHOFF.INTL.HDG	2005-02-04	-0.05	0.2978
306	HENKEL.PREF.	2006-05-22	0.11	0.2471
307	VOLKSWAGEN.PREF.	1996-12-18	0.14	0.3474
308	AHLERS.PREF.	1996-12-18	-0.03	0.2772
309	AVES.ONE	1996-12-18	-0.14	0.2811
310	BAYWA.REGD.	2016-11-28	0.14	0.3554
311	BIOTEST.PREF.	2000-05-17	0.17	0.3884
312	BMW.PREF.	1999-04-06	0.11	0.3045
313	CECONOMY.PRF	1997-12-02	0.05	0.368
314	DRAEGERWERK	1997-12-02	0.02	0.2771
315	FUCHS.PETROLUB.PF.	2010-06-21	0.21	0.2801
316	LINDE..TENDERED. SHARES	1998-10-29	0.18	0.2733
317	METRO.PREF.	2017-08-17	-0.38	0.1969
318	RWE.PREF.	2017-07-13	0.00	0.303
319	SARTORIUS.PREF.	1996-12-18	0.31	0.3636
320	SIXT.PREF.	1999-04-28	0.12	0.3793
321	WESTAG...GETALIT PREF.	1998-10-23	0.06	0.2816
322	ROY.CERAMICS.SE DEAD...02.05.17	2000-01-03	-0.11	0.9463
Panel B. Bond Indices				
1	BD.BENCHMARK.10.YEAR.DS.GOVT	1988-12-30	0.01	0.0398
2	BD.BENCHMARK.30.YEAR.DS.GOVT	1988-12-30	0.03	0.0845
3	BD.BENCHMARK.2.YEAR.DS.GOVT	1994-01-31	-0.02	0.0066
4	REX.GENERAL.BOND	1988-12-30	-0.01	0.0238
5	BD.BENCHMARK.10Y.DS.GVT...IBOXX.	1995-01-02	0.01	0.0389
6	REX.BOND.SUB.INDEX.CURRENT.10.YRS.	2000-12-29	0.00	0.0407
7	BD.BENCHMARK.3.YEAR.DS.GOVT	2004-01-15	-0.02	0.0111
8	BD.BENCHMARK.5.YEAR.DS.GOVT	1988-12-30	-0.01	0.0215
9	IBOXX.EURO.GERMANY.COVERED.CAPPED.5.7	1988-12-30	0.02	0.013
10	IBOXX.EURO.GERMANY.1.10	2010-02-15	0.00	0.0142
11	BD.TOTAL.3.5.YEARS.DS.GOVT	2007-01-08	-0.02	0.0165
12	BD.TOTAL.7.10.YEARS.DS.GOVT	1988-12-30	0.00	0.0344
13	BD.TOTAL.ALL.LIVES.DS.GOVT	1988-12-30	-0.01	0.0267
14	BD.TRACKER.OVER.10Y.DS.GOVT	1988-12-30	0.02	0.0664
15	FTSE.GLOBAL.GOVT..BD.ALL.MATS..E.	1988-12-30	-0.01	0.0275
16	IBOXX.EURO.GERMANY.COVERED.CAPPED	1998-05-01	0.01	0.0085
17	IBOXX.EURO.GERMANY.1.3	2010-02-15	-0.03	0.0054
18	IBOXX.EURO.GERMANY.3.5	1998-12-31	-0.02	0.0159
19	IBOXX.EURO.GERMANY.7.10	1998-12-31	0.00	0.0344
20	IBOXX.EURO.GERMANY	1998-12-31	-0.01	0.0268
21	REX.BOND.SUB.INDEX.CURRENT.3.YRS	1998-12-31	-0.01	0.0137
22	REX.BOND.SUB.INDEX.CURRENT.5.YRS	1988-12-30	-0.01	0.0231
23	REX.BOND.SUB.INDEX.CURRENT.7.YRS	1988-12-30	-0.00	0.0306
24	BD.BENCHMARK.20.YEAR.DS.GOVT	2007-01-02	0.01	0.0615
25	BD.BENCHMARK.7.YEAR.DS.GOVT	1993-11-30	-0.00	0.0288
26	BD.TOTAL.1.3.YEARS.DS.GOVT	1988-12-30	-0.03	0.0061
27	BD.TOTAL.5.7.YEARS.DS.GOVT	1988-12-30	-0.01	0.025
28	BD.TOTAL.OVER.10.YRS.DS.GOVT	1988-12-30	0.02	0.066
29	BD.TRACKER.1.3.YEARS.DS.GOVT	1988-12-30	-0.03	0.0063
30	BD.TRACKER.3.5.YEARS.DS.GOVT	1988-12-30	-0.02	0.0168
31	BD.TRACKER.5.7.YEARS.DS.GOVT	1988-12-30	-0.01	0.0252
32	BD.TRACKER.7.10.YRS.DS.GOVT	1988-12-30	0.00	0.0345

33	BD.TRACKER.ALL.LIVES.DS.GOVT	1988-12-30	-0.01	0.0319
34	EB.REXX.MONEY.MARKET.INDEX	1988-12-30	-0.03	-1e-04
35	EXANE.ECI.GERMANY..CONVERTIBLE....TOT.RETURN.IND	2003-06-30	0.06	0.0667
36	EXANE.ECI.GERMANY..UNDERLYING....TOT.RETURN.IND	1997-01-03	0.10	0.1747
37	FTSE.GLOBAL.GOVT..BD.1.3Y..E.	1997-01-03	-0.03	0.0056
38	FTSE.GLOBAL.GOVT..BD.10.Y..E.	1998-05-01	0.01	0.0667
39	FTSE.GLOBAL.GOVT..BD.3.5Y..E.	1998-05-01	-0.02	0.0161
40	FTSE.GLOBAL.GOVT..BD.5.7Y..E.	1998-05-01	-0.01	0.0248
41	FTSE.GLOBAL.GOVT..BD.7.10Y.E.	1998-05-01	0.00	0.0342
42	FTSE.PFANDBRIEF.BD.1.3Y..E.	1998-05-01	-0.02	0.0051
43	FTSE.PFANDBRIEF.BD.3.5Y..E.	1999-10-01	-0.01	0.0134
44	FTSE.PFANDBRIEF.BD.5.7Y..E.	1999-10-01	-0.00	0.022
45	FTSE.PFANDBRIEF.BD.7.10Y.E.	1999-10-01	0.01	0.0296
46	FTSE.PFANDBRIEF.BD.ALL.MATS..E.	1999-10-01	-0.01	0.0119
47	IBOXX.EURO.GERMANY.COVERED.CAPPED.1.3	1999-10-01	-0.01	3e-04
48	IBOXX.EURO.GERMANY.COVERED.CAPPED.3.5	2010-02-15	0.00	0.0062
49	IBOXX.EURO.GERMANY.COVERED.CAPPED.7.10	2010-02-15	0.03	0.0212
50	IBOXX.EURO.SOVEREIGNS.GERMANY.CAPPED.1.5	2010-02-15	-0.01	0.0043
51	IBOXX.EURO.SOVEREIGNS.GERMANY.CAPPED.10.	2009-11-02	0.05	0.0545
52	IBOXX.EURO.SOVEREIGNS.GERMANY.CAPPED.5.10	2009-11-02	0.02	0.0219
53	IBOXX.EURO.LIQUID.GERMANY.COVERED.DIVERSIFIED	2009-11-02	0.01	0.0082
54	IBOXX.EURO.GERMANY.1.5	2009-12-16	-0.01	0.007
55	IBOXX.EURO.GERMANY.10.	2007-01-08	0.01	0.0662
56	IBOXX.EURO.GERMANY.5.10	1998-12-31	0.02	0.0265
57	IBOXX.EURO.GERMANY.5.7	2007-01-08	-0.01	0.0245

A.2 Further Measures for the Basic Strategies

In Table 7, we present higher order statistics and financial figures for the 50/50 CS and TS strategies. The skewness, kurtosis and drawdown are calculated by the functions implemented in the R package `PerformanceAnalytics`.

We complement our data by market values and book-to-market values per share outstanding also obtained from Datastream. In order to adjust for risk, we obtain alphas for the strategies by two diverse time-series regressions. First, we only account for market risk using the CAPM:

$$R_t^{strat} = \alpha_{CAPM} + \beta R_t^m + \varepsilon_t,$$

before we also consider factors related to size (SMB_t) and book-to-market equity (HML_t) according to Fama and French (1993):

$$R_t^{strategy} = \alpha_{FF3} + \beta_1 R_t^m + \beta_2 SMB_t + \beta_3 HML_t + \varepsilon_t,$$

where for $i \in 1,2,3$ β_i denote the coefficients and ε_t the error term of the regression.

A.3 Volatility Scaling

In contrast to Goyal and Jegadeesh (2017), who define the dollar size of the long and short position of the TS strategy by

$$€Long = \frac{1}{N} \sum_{R_{it-1} \geq 0} \frac{40\%}{\sigma_{it-1}} \text{ and } €Short = \frac{1}{N} \sum_{R_{it-1} < 0} \frac{40\%}{\sigma_{it-1}},$$

we scale the positions to an €1 investment in total such that we get

$$\$Long = \frac{1}{\sum \frac{40\%}{\sigma_{it-1}}} \sum_{R_{it-1} \geq 0} \frac{40\%}{\sigma_{it-1}} \text{ and } \$Short = \frac{1}{\sum \frac{40\%}{\sigma_{it-1}}} \sum_{R_{it-1} < 0} \frac{40\%}{\sigma_{it-1}}.$$

Further, we construct the scaled market index $\bar{R}_t^{scaled}$ as follows

$$\bar{R}_t^{scaled} = \frac{\sum_i \frac{40\%}{\sigma_{it-1}} \cdot R_{it}}{\sum_i \frac{40\%}{\sigma_{it-1}}}.$$

A.4 Tests on Equality

We test for equality of average returns, average long positions and turnover and receive the t-statistics presented in Table 8.

A.5 Turnover Regressions

In order to evaluate whether return differences between strategies can be explained by differences in transaction costs, we regress the difference in turnover numbers of two strategies on the difference in returns. Results are presented in Table 9. We find no evidence for the considered hypothesis.

A.6 Purely Levered Portfolios

Aiming to grasp the effect of time-varying volatility leveraging of the portfolios, we invest in "purely levered" portfolios, where the investment in risky assets is set equal

Table 7: Descriptive statistics for 50/50 CS and TS strategies

Panel A. Descriptive statistics for 50/50 CS strategies

const	1×1	1×6	1×12	6×1	6×6	6×12	12×1	12×6	12×12
α_{FF3}	0.0252	0.0106	0.0429	0.055	0.0197	0.0731	0.0125	0.0698	0.0210
	(0.217)	(0.037)	(0.840)	(0.517)	(0.704)	(1.393)	(0.817)	(2.335)	(3.911)
Median	0.0011	0.0122	0.0098	0.0018	0.0156	0.0265	0.0035	0.0211	0.0375
SD	0.0356	0.0823	0.1373	0.0326	0.0806	0.1394	0.0457	0.0868	0.1410
SR	0.0577	0.2145	0.1986	0.0806	0.2456	0.2425	0.0814	0.1581	0.1889
Skew	1.5873	0.6521	0.9074	0.0786	1.1971	-0.2164	4.0690	-2.8371	-0.9634
Kurt	19.298	3.905	4.836	10.301	8.436	5.429	63.555	12.707	5.233
DD	0.2162	0.6327	0.8609	0.2873	0.5992	0.9777	0.5002	0.9757	0.9983

Panel B. Descriptive statistics for 50/50 TS strategies

const	1×1	1×6	1×12	6×1	6×6	6×12	12×1	12×6	12×12
α_{FF3}	0.0378	-0.1763	-0.0549	0.0708	0.0662	0.0237	0.0077	0.0333	0.0164
	(0.514)	(-1.077)	(-0.001)	(0.785)	(0.316)	(0.628)	(0.071)	(1.245)	(3.465)
Median	-0.0014	-0.0549	0.0059	0.0026	0.011	0.0237	0.0041	0.0198	0.0324
SD	0.023	0.0474	0.0727	0.0276	0.0602	0.1004	0.0327	0.0783	0.1238
SR	-0.1018	-0.0768	0.1282	0.1045	0.1986	0.2193	0.092	0.0963	0.1462
Skew	1.9749	-0.031	-1.2284	1.428	2.476	-0.7025	1.07	-3.1856	-1.5518
Kurt	23.121	4.719	6.021	9.646	18.084	10.778	26.424	14.174	7.243
DD	0.5045	0.7928	0.8052	0.218	0.4184	0.9123	0.4158	0.9677	0.9969

Table 7 presents the annualized alphas obtained in the Fama and French (1993) three-factor model (α_{FF3}), the median, the standard deviation (SD), the Sharpe ratio (SR), the skewness (Skew), the kurtosis (Kurt) and the maximum drawdown (DD) of the 50/50 CS and TS strategies for the holding and ranking periods 1, 6 and 12. Numbers in parentheses are the corresponding t-statistics.

Table 8: T-statistics of the tests on equality

const	1×1	1×6	1×12	6×1	6×6	6×12	12×1	12×6	12×12
Panel A. 50/50 strategies									
50/50 CS = 50/50 TS	1.657	3.545	2.736	-0.097	1.221	1.061	0.199	0.818	0.694
50/50 CS = BAH	-0.359	-0.152	-0.55	-0.009	0.276	0.145	0.193	-0.142	-0.302
50/50 TS = BAH	-1.559	-2.364	-2.642	0.057	-0.491	-0.662	0.042	-0.725	-0.869
Panel B. Time-varying strategies									
TV CS = TV TS	-0.561	-0.81	-1.709	-0.457	-0.478	-0.623	-0.258	-0.146	0.028
TV CS = 50/50 CS	-0.952	-2.871	-3.16	-0.711	-2.453	-1.815	-0.42	-0.439	-1.22
TV CS = 50/50 CS	1.171	0.499	0.68	-0.315	-1.159	-0.37	0.004	0.422	-0.652
50/50 CS = TV TS	0.486	2.46	1.884	0.217	2.045	1.271	0.178	0.279	1.258
TV CS = BAH	-1.094	-2.319	-3.14	-0.551	-1.529	-1.344	-0.178	-0.469	-1.3
TV TS = BAH	-0.731	-1.87	-2.05	-0.172	-1.19	-0.876	0.042	-0.347	-1.33
€$LongTS$ = €$LongCS$	20.617	20.484	20.099	7.49	7.295	7.095	5.096	4.995	4.832
€$LongTS = 0.5$	0.88	1.133	1.127	1.25	1.243	1.059	1.017	0.886	0.549
€$LongCS = 0.5$	-39.313	-38.545	-37.713	-9.926	-9.643	-9.547	-6.489	-6.483	-6.603
CS^{TS}= 50/50 CS	-1.007	-1.976	-2.54	-0.477	-1.248	-1.364	-0.246	-0.546	-0.416
CS^{TS} = TV TS	0.557	1.407	1.177	0.021	0.811	0.801	-0.01	0.404	0.447
CS^{TS} = BAH	-0.295	-0.791	-1.018	-0.154	-0.559	-0.219	0.034	-0.001	-0.945
CS^{TVM} = BAH	0.314	0.084	-0.273	0.236	0.084	0.332	0.249	-0.028	-0.485
normed CS^{TVM}=BAH	0.595	0.523	-0.185	0.408	0.426	0.459	0.266	-0.321	-0.559
$CS^{TVM} = CS^{TS}$	0.722	1.145	0.858	0.448	0.786	0.619	0.244	-0.031	0.389
CS^{TVM} = TV TS	1.247	2.621	2.089	0.468	1.563	1.325	0.238	0.306	0.767
$TS^{TVM} = CS^{TVM}$	1.384	-1.696	-1.199	-0.006	-0.987	-1.151	-0.186	-0.377	-0.215
normed CS = TV TS	1.368	2.861	1.803	0.617	1.68	1.215	0.254	-0.079	0.401
TVM = BAH	-0.196	-0.289	-0.24	-0.191	-0.307	-0.239	-0.151	-0.289	-0.267
Panel C. Tests on equality of (unlevered) unscaled and scaled strategies									
€$LongTS$=1	19.147	18.704	18.215	18.724	18.276	17.777	18.513	18.057	17.546
€$LongTS$	0.069	0.071	0.06	-0.014	-0.016	-0.041	-0.024	-0.042	-0.049
CS	0.747	1.062	0.405	0.188	0.312	-0.274	-0.569	-0.293	-0.336
TS	0.192	0.07	0.131	0.507	0.549	0.468	0.199	0.181	0.245
CS^{TS}	0.268	0.419	0.6	0.156	0.389	0.528	-0.053	0.313	0.357
CS^{TVM}	0.562	0.879	0.436	0.177	0.237	-0.141	-0.401	-0.082	-0.168
TV TS	0.048	-0.082	0.136	0.215	0.21	0.348	0.012	0.249	0.227
BAH	0.196	0.289	0.24	0.191	0.307	0.239	0.151	0.289	0.267
Panel D. Tests on equality of levered and unlevered average returns									
sc. 50/50 CS	-0.417	0.842	1.028	0.392	1	1.069	0.616	3.165	2.804
sc. TV TS	1.641	0.883	1.504	0.398	0.057	1.568	0.94	1.779	1.072
sc. CS^{TVM}	0.169	0.564	0.853	1.051	1.153	0.455	1.004	1.955	2.184
sc. BAH	0.196	0.289	0.24	0.191	0.307	0.239	0.151	0.289	0.267
sc. 50/50 TS	-1.504	-0.509	0.16	0.591	1.922	1.703	0.648	0.914	2.135
CS^{TS}	0.794	0.801	1.216	1.002	2.657	4.427	1.603	3.264	3.324
Panel E. Test on equality of turnover									
CS=scaled CS	-2.437	-2.128	-1.803	-13.397	-13.035	-12.825	-12.768	-12.368	-12.023
CS=TS	1.738	1.764	1.632	11.691	11.573	11.602	9.825	9.786	9.554
TS=scaled TS	-17.546	-17.245	-16.816	-17.93	-17.509	-17.122	-18.995	-18.728	-18.37
CS=scaled BAH	35.877	35.818	35.156	13.599	13.486	13.661	5.676	5.708	5.55
TS=scaled BAH	32.602	32.49	32.155	1.097	1.078	1.236	-6.002	-5.958	-5.833
TS=0	57.24	56.886	56.114	26.65	26.175	25.803	23.53	23.157	22.541

Table 8 presents the t-statistics between nearly all discussed strategies for the holding and ranking periods 1, 6 and 12. Scaled strategies refer to the levered scaled strategy as introduced by Moskowitz et al. (2012) and Goyal and Jegadeesh (2017).

Table 9: Slope coefficients of the regression of turnover on return differences

const	1×1	1×6	1×12	6×1	6×6	6×12	12×1	12×6	12×12
CS - sc. CS	0.001	-0.0012	-0.0186	7e-04	0.0021	-0.0205	-0.004	-0.0065	-0.0155
	(0.34)	(-0.21)	(-1.742)	(0.235)	(0.315)	(-1.364)	(-0.847)	(-0.739)	(-0.978)
CS^{TVM} - sc. CS^{TVM}	4e-04	-0.0042	-0.0223	0	-5e-04	-0.0209	-0.0055	-0.0091	-0.0221
	(0.167)	(-0.791)	(-2.296)	(0.003)	(-0.073)	(-1.498)	(-1.292)	(-1.088)	(-1.53)
TS - sc. TS	0.0017	0.0015	7e-04	0.0043	0.012	0.0168	-7e-04	-0.0027	-0.0019
	(1.418)	(0.855)	(0.244)	(1.678)	(2.465)	(2.444)	(-0.275)	(-0.576)	(-0.247)
TS - CS	-0.0064	-0.0069	-0.0614	-0.0041	-0.0057	-0.0164	0.005	-5e-04	-0.0141
	(-1.16)	(-0.452)	(-2.635)	(-0.833)	(-0.393)	(-0.652)	(0.848)	(-0.051)	(-0.864)
sc. TS - sc. CS	-0.0035	-0.0058	-0.0189	0.0041	0.0097	-9e-04	-0.0108	-0.0212	-0.0345
	(-1.049)	(-0.753)	(-1.72)	(1.325)	(0.975)	(-0.045)	(-1.978)	(-2.809)	(-2.29)

Table 9 presents the slope coefficients of the regression $strat1 - strat2$, where the difference in turnover numbers of $strat1$ and $strat2$ is regressed on the difference in returns of these portfolios. The numbers in parentheses are the corresponding t-statistics.

to 0.4 times the inverse sum of volatilities of all assets. Remind that we define levered portfolios as those that invest more than €1 in risky assets (both in long and short positions). Therefore, we obtain returns, reported in Table 10, of

$$R_t^{leveredstrat} = R_t^{leveredstrat} \times \frac{1}{N} \times \sum_{i=0} \frac{0.4}{\sigma_{it-1}}.$$

Table 10: Alphas for purely levered strategies

const	1×1	1×6	1×12	6×1	6×6	6×12	12×1	12×6	12×12
TV TS	0.002	-8e-04	0.0038	0.0044	0.0028	0.0107	0.0055	0.0093	0.0033
	(0.964)	(-0.155)	(0.527)	(1.835)	(0.53)	(1.399)	(2.141)	(1.482)	(0.364)
50/50 CS	0.0015	0.0178	0.0288	0.0025	0.0198	0.0325	0.0053	0.0127	0.0257
	(0.638)	(3.478)	(3.268)	(1.176)	(3.838)	(3.579)	(1.801)	(2.383)	(2.76)
BAH	-0.0038	0.0199	0.0538	-0.0044	0.0192	0.053	-0.0042	0.0191	0.0542
	(-1.55)	(3.874)	(8.323)	(-1.788)	(3.72)	(8.053)	(-1.698)	(3.633)	(8.113)

Table 10 presents the CAPM alphas of those strategies, where the risky investment in each portfolio equals 0.4 times the inverse of the sum of the ex-ante annualized volatility estimates of each included asset. The numbers in parentheses are the corresponding t-statistics.

A.7 Portfolios including Bonds

As our original sample is not well diversified, we merge daily data on 65 bond indices, obtained from Datastream, with our data set and recalculate the portfolios returns.

Results are reported in Table 11. We recognize positive changes in significance of our returns compared to the less diversified sample.

Table 11: Alphas for momentum portfolios of the sample including bond indices

const	1×1	1×6	1×12	6×1	6×6	6×12	12×1	12×6	12×12
50/50 CS	-0.0087	-0.009	-0.0021	0.0016	0.0189	0.0423	0.0052	0.0208	0.0461
	(-1.611)	(-0.435)	(-0.065)	(0.854)	(4.533)	(5.948)	(1.992)	(4.303)	(5.522)
sc. 50/50 CS	0.0276	0.0441	0.0445	0.0276	0.04502	0.046	0.0281	0.046	0.0478
	(1.968)	(4.884)	(1.937)	(5.254)	(1.672)	(7.628)	(2.047)	(2.657)	(1.617)
CS^{TVM}	-0.0185	-0.0183	-0.011	-0.0144	0.0036	0.0278	-0.0139	0.022	0.0279
	(-3.275)	(-0.88)	(-0.331)	(-6.772)	(0.848)	(3.877)	(-5.005)	(0.457)	(3.349)
sc. CS^{TVM}	0.09	0.0074	0.0073	0.091	0.00754	0.00747	0.0093	0.0077	0.0766
	(2.091)	(1.703)	(3.937)	(2.072)	(1.695)	(1.626)	(2.075)	(1.69)	(3.625)
TV TS	0.1098	0.0082	0.0188	0.0038	0.0103	0.0233	0.003	0.0112	0.0227
	(0.364)	(2.063)	(2.84)	(2.292)	(2.631)	(3.461)	(1.453)	(2.699)	(3.214)
sc. TV TS	0.027	0.0043	0.0044	0.00279	0.0043	0.00457	0.0245	0.0463	0.00468
	(2.268)	(7.657)	(5.622)	(6.236)	(6.625)	(7.588)	(4.141)	(1.963)	(5.547)

Table 11 presents the annualized CAPM alphas and their corresponding t-statistics in parentheses. The underlying data set comprises, next to daily data on 320 stocks, 65 bond indices.

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(Anna Martens)