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Time series momentum - An extension of the evidence and implementation of different trading rules and average pairwise correlation

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Abstract

The aim of this master's thesis is to shed further light on the outstanding performance of a diversified time series momentum strategy and to implement and test extensions suggested in the literature.

To adress the former, I discuss rational and behavioural reasons for time series momentum to work and reconstruct and prolong three strategies from Baltas & Kosowski (2013). I find that the monthly time series momentum strategy continues to perform well in more recent years, while daily and weekly time series momentum performance flattened out. When looking at time series momentum return characteristics I find similar results as previous authors, although I do not find statistically significant outperformance in extreme markets for the monthly strategy.

To adress the latter, I implement a significant trend trading rule (TREND) and a moving average trading rule (MAR) alongside the standard time series momentum trading rule (SIGN) and a correlation adjusted time series momentum strategy (CATSMOM). My results show that by using the TREND rule it is possible to earn higher returns at the cost of higher risk and by implementing CATSMOM investors can lower the risk of the strategy at the cost of higher transaction costs. The MAR rule does not provide investors with any improvements.

Inhalt

Das Ziel dieser Masterarbeit ist es die außergewöhnliche Performance einer diversifizierten Time Series Momentum Strategie näher zu beleuchten und in der Literatur erwähnte Erweiterungen zu implementieren und zu testen.

Dazu diskutiere ich rationale und verhaltensökonomische Ursachen die dazu führen, dass die Strategie für Investoren gewinnbringend ist und ich rekonstruiere und verlängere drei Strategien auf Basis von Baltas & Kosowski (2013). Die Auswertung zeigt, dass die monatliche Time Series Momentum Strategie auch in den letzten Jahren sehr hohe Renditen erziehlt hat, während die tägliche und wöchentliche Strategie kaum zugelegt haben. Im Vergleich zu anderen Arbeiten finde ich ähnliche Eigenschaften der Renditen, allerdings kann ich für die monatliche Time Series Momentum Strategie keine signifikanten Überrenditen in extremen Marktphasen finden.

Als Erweiterungen implementiere ich zwei alternative Handelsstrategien zur Standardregel (SIGN) – eine auf ausschließlich signifikanten Signalen basierende Regel (TREND) und eine Regel, die anhand des gleitenden Durchschnittspreises Kauf- und Verkaufentscheidungen trifft (MAR) – als auch eine korrelationsadjustierte Time Series Momentum Strategie (CATSMOM). Meine Ergebnisse zeigen, dass anhand TREND eine höhere Rendite auf Kosten eines höheren Risikos erziehlt werden kann und dass durch die Implementierung von CATSMOM zwar höhere Transaktionskosten entstehen, die Risiken der Time Series Momentum Strategie allerdings gesenkt werden. Im Gegensatz dazu liefert MAR keinen Mehrwert für Investoren.

Acknowledgements

From June 2012 to May 2014 I had the opportunity to be part of the Portfolio Management Program at Vienna University of Economics and Business where I had the chance to acquire asset management skills by having direct experience in running a real portfolio alongside highly motivated students and under the guiding supervision of financial academics and professional asset managers. Following this great experience I started as a Research Assistant for the Research Institute for Capital Markets, which in collaboration with POK Pühringer Privatstiftung and ZZ Vermögensverwaltung is developing asset management strategies which contribute to successful asset management for university endowments. In this position, my main responsibility was to quantitatively implement trading strategies and one of my main projects during the time at the institute is therefore presented in this master's thesis.

Today, I feel honored to count between the few students that were accepted in the Portfolio Management Program and had the possibility to take part in this challenging yet rewarding program. I would therefore like to thank all people engaged in the program, especially the sponsor Peter Pühringer, the professors Engelbert Dockner, Neal Stoughton and Josef Zechner, as well as Otto Randl and the staff from ZZ Vermögensverwaltung (particularly to my tutor Georg Cejnek) for their great support. Without the participation in the program I would have missed out in gaining a lot of knowledge, but also enjoying great moments together.

The program enabled me to work at the Research Institute for Capital Markets, where this thesis came into existence. Therefore, I would like to address my thanks to all my former colleagues for their support, especially to Richard Franz, who inspired me to write this thesis and was always there for feedback and whenever help was needed. Further, I would like to thank my supervisor Prof. Andrea Gaunersdorfer for her insightful advice and for her promptness, whenever questions arose. This thesis would not have been as comprehensive without their continuous encouragement to always look deeper.

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List of Abbreviations

CAPM	Capital Asset Pricing Model
CATSMOM	Correlation adjusted time series momentum
CBOT	Chicago Board of Trade
CME	Chicago Mercantile Exchange
CSMOM	Cross sectional momentum
CTA	Commodity Trading Advisor
FX	Foreign exchange
HML	"High minus low" risk factor (value)
MA	Moving average
MAR	Moving average trading rule
MDD	Maximum drawdown
Mkt-Rf	Market risk factor
MOM	Cross sectional equity momentum risk factor
OLS	Ordinary least squares
OPEN	Opening jump volatility estimator
RS	Rogers & Satchell (1991) volatility estimator
RV	Realized volatility
SIGN	Sign trading rule
SMB	"Small minus big" risk factor (size)
SR	Sharpe Ratio
STDEV	Standard deviation volatility estimator
TREND	Significant trend trading rule
TSMOM	Time series momentum
UMD	Carhart (1997) "up minus down" risk factor (cross sectional momentum)
YZ	Yang & Zhang (2000) volatility estimator

1. Introduction

Modern Portfolio Theory started with the revolutionary work of Harry Markowitz and his famous article on "Portfolio Selection" from 1952 and underwent many adaptions and further developments since its first appearance in finance. In recent years, financial literature has performed a shift from diversifying over individual assets and asset classes to a diversification over different risk (or style) factors. This view got increasingly popular after the publication of Eugene Fama and Kenneth French's work on "Common risk factors in the returns on stocks and bonds" from 1993. Since then, much work has been done to identify such risk factors for various asset classes. Some of the most prominent of these new strategies[1] are value, carry and momentum. This master's thesis will focus on the last, namely momentum.

Momentum strategies exist in two forms, cross sectional momentum and time series momentum. Cross sectional momentum can be simply described as "winners minus losers" (Jegadeesh & Titman, 1993), i.e. going long the best performers of a given basket of assets and going short the worst performing assets. Whether an asset is bought or sold depends on the relative performance of it compared to the other assets, no matter how the asset performed in absolute terms. A strategy based on that is in theory zero cost (excl. transaction cost), since the long positions can be financed by the short positions. Time series momentum on the other hand is best described by its synonym "trend following", i.e. a strategy that buys an asset if the performance was positive over a certain lookback period and sells the asset if the performance was negative, no matter how the asset performed relative to the other assets in the basket. While cross sectional momentum has been researched extensively over the last two decades, time series momentum is still relatively new to academia.

[1]Risk factors or style factors cannot only explain excess returns of financial assets, they can also be implemented as trading strategies to harvest the risk premias they promise. Therefore, "strategy" is a synonym often used by authors in the financial literature for a risk factor or style factor which is implemented as a trading strategy.

1.1 Motivation

Time series momentum strategies have proven to deliver substantial diversification benefits and provided impressive returns especially in extreme market environments e.g. during the financial crisis of 2008 (Baltas & Kosowski, 2013). They are also able to explain the high alphas of Commodity Trading Advisors (CTAs), which did very well in the downturn following the financial crisis and attracted a huge amount of capital thereafter.[2] In comparison with cross sectional momentum strategies, which are prone to sudden crashes, time series momentum strategies can be used as hedge against tail events and even further are able to capture most of cross sectional momentum while offering higher profits (Moskowitz et al., 2012). In addition, time series momentum returns are statistically distinct from other risk factors such as Fama and French's (1993) market factor, value (HML or "high minus low") and size (SMB or "small minus big") factors (Baltas & Kosowski, 2013).[3] Therefore, time series momentum offers great opportunities to investors and is particularly interesting to implement in a well diversified portfolio. Another reason why it is worth looking at time series momentum from a theoretical perspective is that it challenges the random walk hypothesis stemming from Bachelier (1900) and popularized by Burton Malkiel's book "A Random Walk Down Wall Street" (1973). It states that stock prices move randomly and therefore cannot be predicted, hence trends in prices should not exist. The efficient market hypothesis, formulated by Fama (1970, 1991), further develops the random walk hypothesis by saying that past market information must be useless in predicting future price moves, since all public available information should be already reflected by prices. Accordingly, trend following cannot be profitable in an efficient market following the definition of Fama (1970, 1991).

In some sense, time series momentum looks too good to be true. It yields high returns with low risk and provides substantial diversification benefits to other risk

[2]CTAs (or Managed Futures Funds) are a subgroup of the hedge fund industry and are primarly trading derivatives such as options and futures – both on the long and the short side. According to Joenväärä et al. (2012) CTAs account for around 10–15% of the total number of active hedge funds.

[3]The factors from Fama & French (1993) are available online on the website of Kenneth R. French `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html` (access date: 2016-02-29). The market factor is given by the return of a value-weighted portfolio of all firms in the CRSP database incorporated in the US minus the 1 month T-bill rate. HML and SMB are constructed as market neutral long/short portfolios. Further details are available on the website.

factors especially in times of market stress, when diversification is needed the most (Moskowitz et al., 2012). Therefore, it is worth to have a closer look at the strategy and its extensions, to discuss the results found by other authors and to add further evidence with more recent data on its performance and characteristics.

1.2 Goals and outline

The first goal of this master's thesis is to provide an overview about the existing time series momentum literature and literature that tries to explain the reasons behind its working. Therefore, chapter 2 starts with a short summary of risk factor literature with a focus on momentum and continues with a more comprehensive look on time series momentum. It describes the underlying principle and reasons for its working and addresses the discrepancy of time series momentum and the efficient market hypothesis.

Chapter 3 continues by describing how the strategy is constructed in relevant papers and goes further to explain possible extensions to improve the performance of time series momentum strategies.

Baltas & Kosowski (2013) construct three time series momentum benchmark portfolios on daily, weekly and monthly basis, which are accessible on their website.[4] Unfortunately, their time series stops in January 2012. Therefore, the second goal is to prolong the time series and check, whether it is still profitable. Chapter 4 presents and summarizes the data used in chapter 5 to reproduce the time series momentum benchmarks from Baltas & Kosowski (2013) with the same data sample but from different data providers and to test, whether the strategy still works for more recent observations. This is particularly interesting, since Baltas & Kosowski (2013) find that the rolling Sharpe Ratios of their time series momentum portfolios turn negative at the end of the sample period. I will also reproduce the characteristics of time series momentum described by various time series momentum papers and check, whether they are still valid for data up to June 2015.

Time series momentum seems not to work that well in some market environments as for example in the aftermath of the financial crisis of 2008. In chapter 6 I will adress

[4] `http://www3.imperial.ac.uk/riskmanagementlaboratory/risklabsections/centreforhedgefundsresearch/baltas_kosowski_factors` (access date: 2016-02-29)

this issue by implementing the extensions suggested in chapter 3 and test if and how they affect the performance of time series momentum strategies. Baltas & Kosowski (2012) propose a different signal for the strategy that only invests when prices are significantly trending and Marshall et al. (2014) claim that a moving average based trading rule can significantly improve time series momentum returns. Baltas & Kosowski (2014) modify the time series momentum strategy by incorporating an average pairwise correlation factor to the weighting scheme.[5] Hence, the third goal of the thesis is to improve the risk/return profile of the strategy. Chapter 7 concludes by summarizing the findings.

[5]Following the methodology of Moskowitz et al. (2012), Baltas & Kosowski (2013) weight the single assets used to construct the strategy such that their volatility is scaled to a certain target volatility. This has many advantages as I will show later.

2. Understanding time series momentum

Time series momentum is one of the longest pursued investment strategies in the history of the stock market. There exists written evidence that already 200 years ago traders exploited stock momentum and even one of David Ricardo's three golden investment rules alludes to trend following (Hurst et al., 2012). Even so, it did not get much attention from academia until recently and is mostly covered only by literature on technical trading.

2.1 Risk factor investing

The academic interest in risk factor investing started with Fama & French (1992) criticizing the then still widely accepted Capital Asset Pricing Model (CAPM), which was developed in the 1960s by Treynor (1962), Sharpe (1964), Lintner (1965) and Mossin (1966). In the CAPM, expected returns are a linear function of the market beta and all other risk is assumed to be idiosyncratic and can therefore be diversified away by holding the market portfolio. In contrast, Fama & French (1993) find three factors that can predict returns of stocks, the market factor, firm size (SMB or "small minus big") and value (HML or "high minus low"). Other authors added more factors over the years, such as momentum (Jegadeesh & Titman, 1993; Asness, 1994; Moskowitz et al., 2012), low-beta (Black, 1972; Frazzini & Pedersen, 2014) and carry (Fama, 1984). Additionally there exist other factors that can explain excess returns such as illiquidity (Pastor & Stambaugh, 2003), volatility (Ang et al., 2004) or arbitrage-type trades. Most of these factors can be found in a variety of asset classes (Asness et al., 2012; Koijen et al., 2015) and across international markets (Fama & French, 2012) and most importantly, they are either uncorrelated or negatively correlated with each other (Asness et al., 2015). Risk factors play an important role in explaining excess returns, which is still one of the most important academic playgrounds in finance. The better understanding of such return drivers has had a big impact on asset managament over the years. Recently, practitioners as well as academics get increasingly interested in combining some of these different risk factors into strategies to improve portfolio returns and risk. Many practitioners perform a shift from diversifying over individual assets and asset classes to a diversification over different risk factors, since this has clear benefits for the risk/return profile of their portfolios.[6] With such an approach, portfolio returns can be better understood and asset managers can filter for risk they do or do not want to bear.

2.2 Momentum strategies

Momentum is one of the risk factors mentioned above and was first described by Jegadeesh & Titman (1993). As a reaction to their work a whole new literature branch arose to cover this style factor. Momentum is particularly interesting for practitioners as well as for academics. For practitioners its outstanding returns and diversification benefits are attractive, while for academics it is another puzzle to solve, since the mechanisms behind it are not yet fully understood (Daniel & Moskowitz, 2013). Momentum has been found in all possible markets, for US equity (Jegadeesh & Titman, 1993; Asness, 1994) and international equity (Rouwenhorst, 1998; Fama & French, 2012), in currency markets (Shleifer & Summers, 1990; Burnside et al., 2011; Menkhoff et al., 2012), commodity markets (Miffre & Rallis, 2007; Shen et al., 2007, 2010) and futures (Pirrong, 2005) and basically everywhere (Asness et al., 2012).

The early works on momentum cover only one type of it, namely cross sectional momentum. As its name suggests, it is a form of momentum which takes the relative performance of an asset to determine whether a long or short position should be taken. To construct the strategy an investor considers a basket of assets and buys those that performed best over a certain time period while assets that performed worst are sold, no matter on how good or bad the assets performed. Cross sectional momentum is therefore also sometimes called "winners minus losers" (Jegadeesh & Titman, 1993). Time series momentum on the other hand uses the absolute performance of each asset as a decision rule for a long or short position in the asset. Whenever the performance

[6] See for example Asness et al. (2015) for a summary of the benefits and an implemenetation of such a strategy.

was positive over a certain time period the asset is bought, if the performance was negative it is sold, independent of the behavior of the other assets. A synonym for time series momentum is “trend following”.

Time series momentum became popular in the academic world only recently due to the work of Moskowitz et al. (2012). While there exists some earlier work on the topic, it comes mostly from traders using technical analysis for trading decisions.[7] This investment style is frowned upon by the mainstream academic literature and therefore trend following remained longtime a niche topic.

2.3 The economics of time series momentum

There has been a vivid discussion among academics about the consistency of risk factors and even though many have been discovered over the years, only a few are broadly accepted in the academic world as well as used in practice by asset managers. A prominent example is Fama and French’s 1993 size factor (SMB) which proved to be less successful in later robustness tests and got abandoned over time (Knez & Ready, 1997). Due to the fact that financial markets cannot be reproduced in laboratory experiments it is hard to distinguish random correlations from robust patterns in the data, making it difficult to prove the consistency of such patterns. Financial academics developed a name for the process of scouring financial data for relationships that might be consistent or not, namely data mining. It can be avoided by first formulating a hypothesis and then testing it and not the other way around.[8]

Accordingly, it is necessary to find either rational or behavioral reasons why the underlying principle does work and why it should continue to work after publication. What makes it especially interesting for time series momentum though is the fact that its existence challenges the efficient market hypothesis from Fama (1970, 1991) and

[7] Brock et al. (1992), Lo et al. (2000), Zhou & Zhu (2009) or Han et al. (2011) all use moving average trading rules or other technical rules as signal for trend following and report substantial returns. Menkhoff & Taylor (2007) provide a survey of technical analysis literature for time series momentum in FX markets and Szakmary et al. (2010) compare cross sectional momentum returns with time series momentum strategies using a dual moving average crossover rule as well as a channel rule for commodity futures. In chapter 6.3 I implement a simple moving average trading rule that is described in chapter 3.2.1 and see how it performs compared to other trading rules.

[8] This is not just a problem of the recent financial literature but was already a topic of interest for early financial authors. Benington & Jensen (1970) provide an early work on the topic.

finding reasons for time series momentum to work is identical with finding arguments against the efficient market hypothesis.

2.3.1 The random walk and efficient market hypothesis

The random walk hypothesis goes back to Bachelier (1900). He argues that stock prices move randomly and therefore cannot be predicted by past price movements. Fama (1970, 1991) extends this notion to the so called efficient market hypothesis. He distinguishes three types of market efficiency. The first and weakest form states similar to the random walk theory that future price moves cannot be predicted by past price moves. The semi-strong form suggests that all publicly available information relevant for the price of an asset is already priced in and therefore no advantage can be achieved by doing fundamental research. The strongest form of market efficiency claims that not only publicly available but also only privatly available information is already reflected by prices, making it impossible to earn on any form of market information.[9]

Even the weakest form of market efficiency suggests therefore that time series momentum should not work in practice. Financial academics are still debating over the existence of market efficiency and some studies find arguments against it while others find supporting results. To account for all the criticism a new notion of market efficiency has been developed that might be compatible with time series momentum returns, a notion of market efficiency that allows for time varying risk premias.[10] This means, that above average returns are not possible without accepting above average risk. Moskowitz et al. (2012) show however, that even such a more general version of market efficiency is challenged by a diversified time series momentum strategy due to its robust and stable performance over a long sample period and its high Sharpe Ratio. Even further, they find that time series momentum returns seem no compensation for crash risk, but time series momentum is rather a hedge against tail events, since it performs best in extreme markets.

[9]The strong form of market efficiency is not relevant in today's financial markets, since insider trading is illegal.

[10]A good overview of the ongoing debate as well as a summary of efficient market definitions is presented in Malkiel (2003).

If time series momentum is consistent with the efficient market hypothesis, there must be a rational reason why it is profitable and this reason must be some form of risk compensation. If on the other hand the reason for its working is of a behavioural nature and due to market inefficiencies or human psychology, this would contradict any form of market efficiency.

Another important aspect when looking at the underlying principle is the fact that finding a rational reason for the strategy to work implies that the strategy should continue to work in the future, while behavioural reasons can be arbitraged away. A recent article by Cliff Asness (2015) discusses this topic in detail.

2.3.2 The underlying mechanism of time series momentum

The underlying principle of time series momentum is a trend in the price of an asset. These trends exist due to an initial under-reaction following a fundamental change in the value of the asset and a delayed over-reaction. Hurst et al. (2013) offer a handy illustration of the process which is reflected in figure 2.1. A catalyst, i.e. a fundamental change in the underlying asset, causes the value of the asset to change. Investors are slow to react and the price of the asset moves only gradually and firstly under-reacts while overshooting later, followed by a reversal. A time series momentum strategy positions the investor accordingly and exploits the continuation of the trend.[11]

2.3.3 Initial under-reaction

There exist many well researched theories that play a role for the observed under-reaction in prices following a fundamental change in value. Edwards (1968) and Tversky & Kahneman (1974) find evidence that people anchor their views on prices to historical price data and are slow in reacting to new information. This price conservativeness causes prices to under-react (Barberis et al., 1998). There exists also evidence that under-reaction is caused by a slow spreading of news (Hong & Stein, 1999).

[11] Cross sectional momentum does to some extend also gain from price trends. If the best performers (which are bought) have a positive past performance and the worst performers (which are sold) have a negative past performance, the investor gains from a continuation of the price trend. Note though, that cross sectional momentum does not look at the absolute performance, which makes it possible to buy assets that performed negative and sell assets that performed positive. In that case a continuation of the trend could hurt the investor.

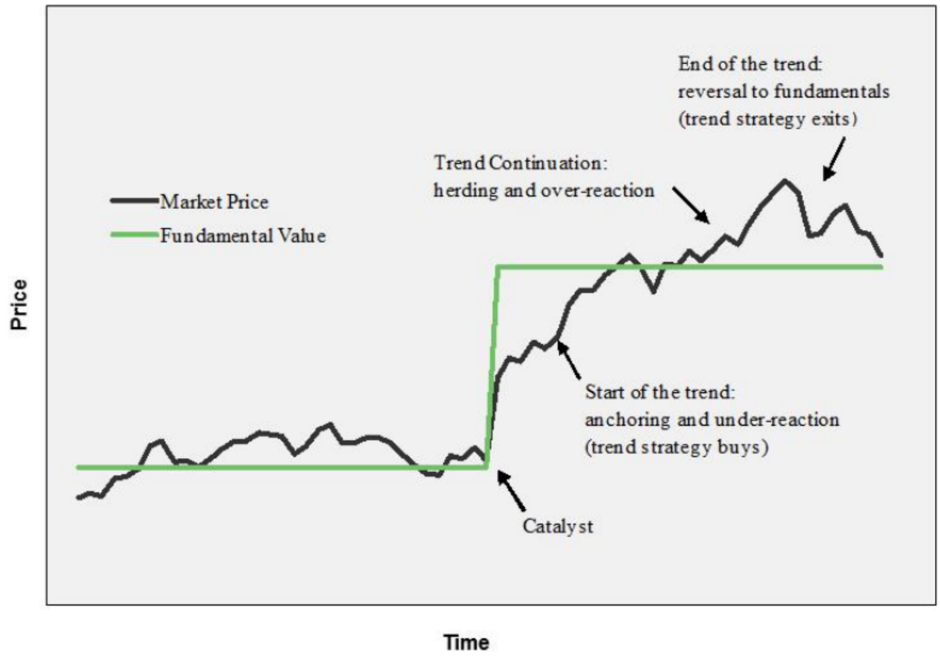

FIGURE 2.1: Lifecycle of a trend. A catalyst, i.e. a change in the underlying asset, causes the fundamental value of the asset to change. Investors are slow to react and the price of the asset moves only gradually and firstly under-reacts while overshooting later, followed by a reversal in the price. The graph is originally from Hurst et al. (2013), figure 1.

Another effect causing under-reaction is the so called diffusion effect. Shefrin & Statman (1985) and Frazzini (2006) find that it is a general phenomenon that investors sell winners too early to realize profits and hold on losers too long to make up for the losses already incurred. This causes both under-reaction in bull markets as well as in bear markets.

Also non-profit seeking activities by certain market participants play a role for the slow reaction to shocks. Central banks for instance try to reduce exchange rate and interest rate volatility to stabilize markets and therefore also cause under-reaction in market prices (Silber, 1994). Funds that mechanically rebalance to keep a certain asset allocation trade against trends, since winners have to be sold and losers have to be bought to keep the weights constant (Hurst et al., 2013) and corporate hedging programs may slow down price movements (Baltas & Kosowski, 2013).

Under-reaction may also be caused by market frictions such as liquidity constraints, regulatory constraints and bureaucratic hurdles. Capital is often only moving slowly between assets and therefore price movements are slower to happen than they should

(Duffie, 2010; Mitchell et al., 2012).

2.3.4 Delayed over-reaction

There exist also a number of possible causes why prices overshoot in the long run such as herding effects and feedback trading. Bikhchandani et al. (1992) show that herding is a phenomenon immanent to the human nature and therefore also investors are prone to it. An asset that performed well over a certain period is more attractive for new investors due to the success other people had with it. Especially analysts are susceptible to herding (Welch, 2000) as well as investment newsletters (Graham, 1999). Feedback trading is a special case of herding and arises when the common signal for the directional trades by herdings investors comes from lagged returns or variables correlated with lagged returns. Even institutional investors seem to exhibit such behaviour (Nofsinger & Sias, 1999; De Long et al., 1999).

Wason (1960) and Tversky & Kahneman (1974) show that people are more likely to look at information that confirms what they already believe. Past price developments are therefore often seen as a representative of future price changes and more money is moved into successful investments while it is withdrawn from losing positions. Overconfidence stemming from successful trades may as well play a role in causing overreaction in asset prices (Daniel et al., 1998) and general market sentiment (Baker & Wurgler, 2006).

Further, fund flows might play a role for over-reaction. While underperforming funds experience fund outflows they have to respond by reducing their underperforming positions and outperforming managers receive inflows and therefore increase their outperforming positions even more. All this puts price pressure on asset prices and will prolong the trend. Moreover, some risk management practices might lead to overreaction as for instance stop-loss orders and hedging activities can increase price pressure as well (Garleanu & Pedersen, 2007). Hurst et al. (2013) list as an example an airline company that might hedge their exposure to kerosene after a surge in prices which in turn again puts upward pressure on future prices.

2.3.5 The rational story

On the other hand there exist also a handful of papers that try to find a rational explanation for the existence of price trends. Brown & Jennings (1989) develop a two-period dynamic equilibrium model and show that historical prices are useful for rational investors to form demands if prices are not fully revealing. Zhou & Zhu (2014) build a continuous-time general equilibrium model with three types of investors, informed investors, technical traders (that follow a simple moving average strategy, i.e. trend followers) and noise traders. In their model, technical traders earn an equilibrium return as they provide a risk-sharing function to market participants. Berk et al. (1999) develop a model that tries to explain two of the common risk factors, value and momentum. They find that changes in a firms expected returns are predictable by past realized returns, causing momentum strategies to be profitable. Similarly, Johnson (2002) builds a simple single-firm model and finds a strong positive correlation between realized and expected returns. Chordia & Shivakumar (2002) show that momentum can be explained by a set of lagged macroeconomic variables and depend therefore on time-varying expected returns. Moskowitz et al. (2012) find that speculators are on average profiting from time series momentum on the expense of hedgers. This might indicate that it is a reward for taking on risk hedgers are not willing to take.

All mentioned theories indicate that time series momentum might as well be due to rational behavior of market participants or at least it cannot be completely ruled out, even if the form of underlying risk is not yet fully clear. This in turn means that there is no clear evidence against the efficient market hypothesis, at least not against a more sophisticated notion.

2.3.6 Return and sign predictability

Time series momentum does only work if future returns can be predicted by past returns or if at least the sign of future returns can be predicted by past returns. Moskowitz et al. (2012) and Baltas & Kosowski (2013) both check for autocorrelation in their return series and find a strong intertemporal return relation. There exists a broad literature that confirms these results, finding positive autocorrelation for shorter horizons and reversals for periods longer than a year (Fama & French, 1988; Lo & MacKinlay, 1988; Poterba & Summers, 1988). New in Moskowitz et al. (2012) and Baltas & Kosowski (2013) is that they vary between lookback and holding period lengths and show that even though they are not the same there exists an even stronger return predictability. The relationship is robust and can be found in various asset classes, subperiods and is even stronger if only sign predictability is tested, which is enough in the case of time series momentum. Moreover, Christoffersen & Diebold (2006) and Christoffersen et al. (2007) show that volatility predictability and return sign predictability are strongly linked, even when no return predictability can be found.

3. Methodology

In this section I present the methodology used to construct the time series momentum strategies. Appendix F additionally provides the corresponding R code. The basic methodology of time series momentum stems from Moskowitz et al. (2012) and is used with small variations also by Baltas & Kosowski (2013) and Hurst et al. (2013). In its simplest form, a time series momentum strategy can be constructed as following:

$$r^{\text{TSMOM}}(t, t+k) = \frac{1}{N_t} \sum_{i=1}^{N_t} \text{SIGN}_{i,t} \cdot r_i(t, t+k), \tag{3.1}$$

where $r_i(t, t+k)$ is the excess return[12] of asset i between t and $t+k$ (k is the holding period) and is multiplied by a factor SIGN, which is defined by a specific trading rule. For the standard version of time series momentum SIGN is $+1$ if the excess return of asset i was non-negative over a given time period j (the lookback period) and -1 else:

$$\text{SIGN}_{i,t} = \begin{cases} +1 & \text{if } r_i(t-j, t) \geq 0 \\ -1 & \text{if } r_i(t-j, t) < 0 \end{cases} \tag{3.2}$$

All single asset time series momentum returns are then summed and devided by the number of traded assets N_t to get an equally weighted portfolio. $r^{\text{TSMOM}}(t, t+k)$ is then the excess return of the time series momentum strategy between t and $t+k$.

3.1 Time series momentum with futures

Moskowitz et al. (2012), Baltas & Kosowski (2013) and Hurst et al. (2013) all use futures contracts to build their time series momentum strategies and this has various benefits. First of all, futures markets are very liquid and transaction costs are fairly small (Moskowitz et al., 2012). In addition they require only a fraction of their notional amount as margin payment, which makes futures highly levered investments. The strategy can therefore be implemented cheaply and liquidity issues usually do not

[12] The calculation of $r_i(t, t+k)$ is explained in more detail in chapter 3.1.

play a role. Moskowitz et al. (2012) show that the correlation between the profitability of a time series momentum strategy and the liquidity of the underlying asset is negative, suggesting that the strategy works better for more liquid assets. Further, it is possible to short futures, which is not possible or very expensive for other asset classes and necessary for the proper implementation of a long/short strategy like time series momentum. Another reason to use futures is the broad spectrum of assets covered by such contracts and the long availability of historical data to test the strategy. Reliable futures price history is available on various data platforms starting in the 1970s and modern futures markets such as the Chicago Board of Trade (CBOT) or Chicago Mercantile Exchange (CME) exist since the mid of the 19th century. Futures are traded on a variety of asset classes, such as commodities, currencies, interest rates or equities but also for more exotic products such as volatility or renewable energy certificates. A strategy with futures can therefore be tested and implemented on multiple asset classes.

Futures are standardized contracts that specify the price and date a buyer agrees to buy a certain asset from a seller. Usually there exist a couple of delivery months per year for each asset, so buyers who do not want to end up with the asset in hand can roll in the next contract by simply selling the old one before its expiry and buying one with a delivery day further in the future. By rolling the futures contract one is exposed to the so called roll yield, since futures of different delivery months usually trade at different prices and futures prices are either above the spot price (called contango) or below the spot price (called normal backwardation). The roll yield is therefore positive or negative depending on whether the futures contract is in (normal) backwardation or contango (given a long position). Over the life cycle of the futures contract its price converges to the spot price. Figure 3.1 plots the futures price curve of the S&P 500 on 1st June 2015. All contracts are in backwardation, since they all trade below the current spot price.

Since futures are short-lived contracts, it is not so straightforward to construct a continuous price time series. Following the method of de Roon et al. (2000), Moskowitz et al. (2012) and subsequent authors form price series by using the most liquid contract for each point in time, measured by traded volume. The price series is roll adjusted, i.e. the historic price series is multiplied by the roll ratio (price of new contract divided

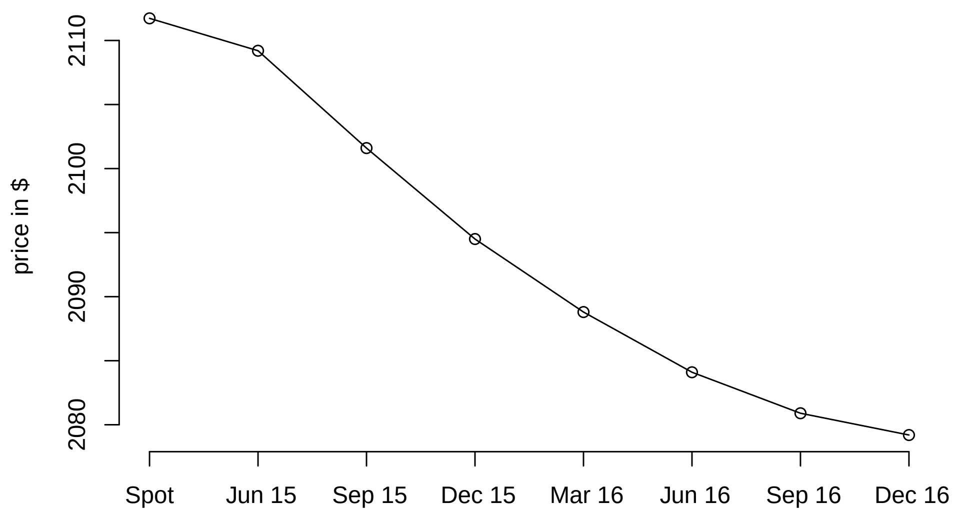

FIGURE 3.1: S&P 500 futures price curve. The plot shows the spot price and S&P 500 futures price curve on 1st June 2015 including the contracts with expiry in June 2015, September 2015, December 2015, March 2016, June 2016, September 2016 and December 2016.

by the price of old contract) at each roll date. This means that all proceeds from selling the old contract are invested in the new contract (for a long position) – futures contracts are therefore assumed to be arbitrarily divisible. If one would roll in the new contract without roll adjusting the price series, the return series would be manipulated depending on whether the futures contract is in backwardation or contango.

After constructing a continuous price series for each asset, one needs to calculate excess returns from it. Let $F_{t,T}$ be the price of a futures contract with delivery date T at time t. M_t is the balance on the margin account required to be able to trade futures at time t, which earns the risk free rate r_t^f, so that between t and $t+k$ the margin account will grow by $M_t(1+r_t^f)+(F_{t+k,T}-F_{t,T})$. The excess return of the futures contract is therefore:

$$r_i(t,t+k) = \frac{[M_t(1+r_t^f)+(F_{t+k,T}-F_{t,T})]-M_t}{M_t} - r_t^f \tag{3.3}$$

To make things easier, Moskowitz et al. (2012) assume that the futures are fully collateralised, i.e. M_t is equal the price of the futures contract at time t, $F_{t,T}$:[13]

$$r_i(t, t+k) = \frac{F_{t+k,T} - F_{t,T}}{F_{t,T}} \tag{3.4}$$

Baltas & Kosowski (2013) also argue in favor for this simplification and it should not affect the results too much, even if it abstracts from some practical properties of futures trading such as potential margin calls, interest accrued on the margin account or the fact that futures positions must not need to be fully collateralised.

3.1.1 Volatility scaling the return series

Having obtained return series from different futures contracts they can be used to form a time series momentum strategy. To make different futures contracts comparable though, it makes sense to scale them by their ex-ante volatility.[14] Futures from different asset classes exhibit big differences in their return distributions, especially in the cross-sectional variation of volatilities. While commodity and equity futures exhibit high volatilities, currencies are less volatile and interest rate futures move the least. The WTI Oil futures contract for instance is almost 25 times as volatile as the German 2Y government bond futures contract (Baltas & Kosowski, 2013). To take account for these large differences it is possible to scale the excess returns by their ex-ante volatilities. According to Hurst et al. (2013) this makes sense due to two important reasons: Firstly to risk adjust the exposures of the strategy to each asset and to not have a few high-volatility assets dominate the portfolio returns. Barroso & Santa-Clara (2012) show that momentum returns are driven by a few high volatility assets if not scaled accordingly. Secondly it ensures that the risk of single assets stays relatively stable over time which is important to keep control in high risk periods. Barroso & Santa-Clara (2012) show that volatility scaling is successful in reducing exposures in periods of stress.

[13]Gorton et al. (2007), Miffre & Rallis (2007), Pesaran et al. (2009), Fuertes et al. (2010), Baltas & Kosowski (2012, 2014) and Hurst et al. (2013) all use the same methodology.

[14]The term "ex-ante volatility" is used as a synonym for "volatility estimator" in the rest of the thesis. Moskowitz et al. (2012) and Baltas & Kosowski (2013) use the same terminology.

Therefore, Moskowitz et al. (2012) implement a volatility scaling factor in the time series momentum strategy from equation 3.1, which makes it possible to scale the exposure to each asset i such that a predefined target volatility level σ_{target} is reached for each asset:

$$r^{\text{TSMOM}}(t, t+k) = \frac{1}{N_t} \sum_{i=1}^{N_t} \text{SIGN}_{i,t} \cdot \frac{\sigma_{\text{target}}}{\sigma_{i,t}} \cdot r_i(t, t+k) \tag{3.5}$$

Equation 3.5 gives the return of a time series momentum strategy in excess of the risk free rate between t and $t + k$, where k is the holding period and N_t is the number of assets in the portfolio and $\text{SIGN}_{i,t}$ is either $+1$ or -1 for each asset i at time t, depending on the performance of asset i over the lookback period j. All single asset positions are scaled such that the ex-ante individual asset volatility is set to σ_{target}. $\sigma_{i,t}$ is the ex-ante volatility estimator of asset i at time t and is explained in more detail in the subsequent chapter. $r_i(t, t+k)$ is the single asset excess return over the holding period k.

Choosing σ_{target} is somewhat arbitrary but it makes sense to adjust it such that the ex-post volatility of the strategy is close to the volatility of most common risk factors to make things comparable. Hence, Moskowitz et al. (2012) use 40% as single asset target volatility for their sample period and dataset. The aggregated time series momentum strategy has then an annualised ex-post volatility of around 12%, which is similar to the volatilities exhibited by other risk factors such as the ones from Fama & French (1993) and Asness et al. (2012). Clearly, it depends on the dynamic correlation structure of the cross-section of assets on how much smaller the aggregated volatility is compared to the target volatility σ_{target}. Therefore, it is not so trivial to choose an appropriate target volatility level. Another reason why to choose 40% is that it is equal to the average volatility of an individual stock according to Moskowitz et al. (2012). Baltas & Kosowski (2014) address this problem with a more sophisticated approach and I will come back to this later in chapter 3.2.2.

Baltas & Kosowski (2013) also choose 40% as target volatility level and end up with 14.88% ex-post volatility for their 12 month lookback 1 month holding period strategy, which is close to the 15.22% volatility of the MSCI World index but slightly above the volatility of other risk factors such as SMB (10.88%) or HML (10.64%) over the same period.

This leads to the following time series momentum strategy used by Moskowitz et al. (2012), Baltas & Kosowski (2013) and Hurst et al. (2013), where $\text{SIGN}_{i,t}$ is defined as in equation 3.2 and $\sigma_{i,t}$ is calculated over a period of 60 days:

$$r^{\text{TSMOM}}(t, t+k) = \frac{1}{N_t} \sum_{i=1}^{N_t} \text{SIGN}_{i,t} \cdot \frac{40\%}{\sigma_{i,t}} \cdot r_i(t, t+k) \tag{3.6}$$

The ex-ante volatility scaling of the single asset returns is necessary to risk adjust the weights of each asset in the aggregate strategy. The method is also used by other cross sectional momentum authors and is especially useful to avoid momentum crashes. Barroso & Santa-Clara (2012) scale their momentum returns by the ex-ante volatility and find that this nearly doubles the Sharpe Ratio of the strategy and effectively eliminates crashes. In chapter 5.1 I show similar results for time series momentum.

3.1.2 The volatility estimator

In the time series momentum literature different types of volatility estimators $\sigma_{i,t}$ are used for volatility scaling. Moskowitz et al. (2012) and Hurst et al. (2013) use exponentially weighted lagged squared daily returns to calculate the ex-ante volatility:

$$\sigma_t^2 = 261 \sum_{i=0}^{\infty} (1-\delta)\delta^i (r_{t-1-i} - \bar{r}_t)^2, \tag{3.7}$$

where δ is chosen such that the center of mass $\sum_{i=0}^{\infty}(1-\delta)\delta^i i = \frac{\delta}{1-\delta}$ is 60 days and $\sum_{i=0}^{\infty}(1-\delta)\delta^i = 1$. Multiplying by 261 (the number of trading days per year) is necessary to get the annualised variance and $\bar{r}_t$ is the exponentially weighted average return and is calculated as following:

$$\bar{r}_t = \sum_{i=0}^{\infty} (1-\delta)\delta^i r_{t-1-i} \tag{3.8}$$

Baltas & Kosowski (2013) use a more sophisticated estimator, the Yang & Zhang (2000) volatility estimator, which is a range based estimator, i.e. it takes the intraday range between high and low price into account. Furthermore, it also adjusts for a drift in the stock price and accounts for the overnight price jump. Its construction is described in appendix A.

Range based estimators have a few advantages over simpler approaches which use only closing price information. Firstly, they are able to detect intraday price volatility. Baltas & Kosowski (2013) give as an example the performance of the FTSE 100 index on 9th August 2011, when intraday prices went from -5.48% to $+2.10\%$ before finally closing up $+1.98\%$. Volatility calculated via the standard deviation does not account for intraday price movement and would show a rather normal trading day. Secondly, Baltas & Kosowski (2012) and Maillet et al. (2009) compare simple estimators such as the sample variance with a pool of range based estimators, including driftless range based estimators such as the Parkinson (1980) and Garman & Klass (1980) estimators, the Rogers & Satchell (1991) estimator that allows for a drift and the Yang & Zhang (2000) estimator, which also takes the opening jump into account. The benchmark they use for their test is the Realized Volatility (RV). It is the sum of N squared returns of arbitrarily small time units Δ and is considered the best available estimator for financial risk:

$$\text{RV} = \sum_{i=1}^{N} r_i^2(t, t+\Delta) \tag{3.9}$$

Both come to the conclusion that range based estimators are good proxies for Realized Volatility and most importantly they are more efficient in estimating volatility than simpler approaches, therefore needing less data to reach the same level of efficiency by reducing the variance of the estimator. Furthermore, Alizadeh et al. (2002) show that range based estimators are robust to microstructure noise such as the bid-ask bounce and asynchronous trading.

Baltas & Kosowski (2014) discuss the impact of different volatility estimators on the performance of time series momentum strategies and they find that except for the Realized Volatility estimator all other estimators do not have an economically significant impact on the performance of the strategy, measured by the Sharpe Ratio. However, when using a more sophisticated volatility estimator the turnover is reduced by around one tenth and this does certainly have an impact on the performance when considering transaction costs. They find that the Yang & Zhang (2000) volatility estimator is by far the best out of the range based estimators both in reducing turnover and in minimizing the forcast bias regarding the Realized Volatility.

3.1.3 Lookback and holding periods

Baltas & Kosowski (2013) test a broad variety of combinations of different lookback and holding periods for monthly, weekly and daily returns. As mentioned in chapter 2.3.6 they find strong return predictability for shorter periods that is robust and highly significant at the 1% level. As other momentum authors did before them, they show that some combinations promise particular high returns and Sharpe Ratios well above 1 and some even higher than 1.2. The strategy they find working best for daily returns is a 15 days lookback and 1 day holding period, for weekly returns it is a 8 weeks lookback and 1 week holding period and for monthly returns a 12 month lookback and 1 month holding period works best, confirming the findings of Moskowitz et al. (2012).[15]

In the rest of this paper I will focus on the same strategies as covered in Baltas & Kosowski (2013). I will call the 15 days lookback and 1 day holding period strategy "daily strategy", the 8 weeks lookback and 1 week holding period strategy "weekly strategy" and the 12 month lookback and 1 month holding period strategy "monthly strategy" thereafter.

3.2 Extensions of time series momentum strategies

Moskowitz et al. (2012), Baltas & Kosowski (2013) and Hurst et al. (2013) find that time series momentum is very profitable and earnes high annual returns over a long period of time. Still, in more recent years and especially after the financial crisis of 2008, its performance flattened out. To adress the low or negative performance of time series momentum in times when price trends are absent, time series momentum literature came up with two major modifications of the strategy. The first is to use a different trading signal and the second is to adjust for the pairwise average correlation of the individual assets.

[15]The performance analysis both Moskowitz et al. (2012) and Baltas & Kosowski (2013) base their strategy choice on is done ex-post by using information the authors would not have had at the beginning of the sample period (so called in-sample optimization). Therefore, the combinations of lookback and holding periods they use in their articles are somewhat questionable and it is not fully clear, whether the outperformance prevails. The analysis still shows that almost all tested combinations are significantly profitable, supporting the main result that time series momentum provides investors with high excess returns, independent of the exact choice of the periods.

3.2.1 Using different trading rules

The time series momentum strategy constructed in chapter 3.1 uses a simple rule for determining if an asset is bought or sold. Equation 3.2 simply looks whether the performance of the asset was non-negative or negative over the lookback horizon, it does not account whether the performance was statistically significant or not. The disadvantage of such a simple SIGN rule is that there might be a lot of noise coming from assets that perform flat and change their sign a lot but do not contribute much to time series momentum performance. Therefore, it might be beneficial to only consider statistically significant trends instead of all of them. Baltas & Kosowski (2012) implement a trading signal that fits a linear trend on the futures price series $F_{t-j+\tau}$ for each time t over the lookback period j using least squares:

$$F_{t-j+\tau} = \alpha_t + \beta_t \cdot \tau + e_{t-j+\tau} \qquad \tau = 1, \ldots, j \tag{3.10}$$

The t-statistic of the beta coefficient $t(\beta_t)$ from this regression can be used to determine whether to buy or sell the asset:

$$\text{TREND}_{i,t} = \begin{cases} +1 & \text{if } t(\beta_t) > +2 \\ -1 & \text{if } t(\beta_t) < -2 \\ 0 & \text{else} \end{cases} \tag{3.11}$$

Newey & West (1987) t-statistics are used to account for the observed autocorrelation and heteroskedasticity in the price process.

Baltas & Kosowski (2012) find that while the TREND signal does not significantly change the performance of the strategy nor the Sharpe Ratio, it decreases turnover by 66.2% resulting in much lower transaction costs. Further, for a bigger proportion of assets TREND is equal to zero in times when the strategy does not perform well and when time series momentum works well the TREND signal behaves similar to the SIGN signal.

Another modification proposed by authors is to use a moving average trading rule (MAR) instead of the SIGN rule. Marshall et al. (2014) argue that moving averages give earlier signals and therefore increase returns of a time series momentum strategy significantly. While sign signals coincide with moving average (MA) direction changes, MA signals only require the price to go above (below) the MA to give a buy (sell) signal. The moving average is constructed as following:

$$\mathrm{MA}_{i,t} = \frac{F_t + \ldots + F_{t-j+2} + F_{t-j+1}}{j}, \tag{3.12}$$

where j is the lookback period and F_t are the futures prices. Therefore the MA signal is

$$\mathrm{MAR}_{i,t} = \begin{cases} +1 & \text{if } F_t - \mathrm{MA}_{i,t} \geq 0 \\ -1 & \text{if } F_t - \mathrm{MA}_{i,t} < 0 \end{cases} \tag{3.13}$$

The SIGN rule and the MAR rule are closely related with each other. SIGN is defined as $\mathrm{SIGN}_{i,t} = \mathrm{sgn}(F_t - F_{t-j})$, where sgn is the sign function that returns the sign of a real number (see equation 3.2). From

$$\mathrm{MA}_{i,t} - \mathrm{MA}_{i,t-1} = \frac{F_t + \ldots + F_{t-j+2} + F_{t-j+1} - F_{t-1} - \ldots - F_{t-j+1} - F_{t-j}}{j} \tag{3.14}$$

follows

$$\mathrm{sgn}(\mathrm{MA}_{i,t} - \mathrm{MA}_{i,t-1}) = \frac{\mathrm{sgn}(F_t - F_{t-j})}{j} = \frac{\mathrm{SIGN}_{i,t}}{j} \tag{3.15}$$

since j is always a positive number and therefore

$$\mathrm{SIGN}_{i,t} = j \cdot \mathrm{sgn}(\mathrm{MA}_{i,t} - \mathrm{MA}_{i,t-1}) \tag{3.16}$$

Whenever $\mathrm{MA}_{i,t}$ changes direction the SIGN signal will change as well. According to Marshall et al. (2014) this usually occurs later than the price moving below the MA or above the MA, since the MA will only change direction after a prolongued change in trend. Thus, they find that MAR is generally an earlier and better indicator than SIGN.

3.2.2 Pairwise correlation

Baltas & Kosowski (2013) report that CTAs that follow time series momentum strategies did not perform that well anymore in the aftermath of the financial crisis, although achieving surprisingly high returns when the market was crashing. They also find that capacity constraints seem not to be the reason for the loss in performance, even if CTAs saw big inflows in those years. Moskowitz et al. (2012) look at the connection between liquidity and market sentiment to explain time series momentum returns. They also find no significant relationship that could explain recent underperformance. What seems a more promising factor in explaining the variation in time series momentum returns are cross asset correlations. Hurst et al. (2012) find that correlations across asset classes and single assets have increased since 2007, decreasing the number of independent trends time series momentum can profit from and therefore lowering the risk adjusted returns.

To account for times with increased cross asset correlations Baltas & Kosowski (2014) add a pairwise correlation factor to the strategy exploiting the relationship between volatility and correlation. Given a portfolio with N assets with weights w_i for each asset i, the portfolio volatility σ_p can be rewritten with the formula for the standard deviation:[16]

$$\sigma_p = \sqrt{\sum_{i=1}^{N} w_i^2 \sigma_i^2 + 2 \sum_{i=1}^{N} \sum_{j=i+1}^{N} w_i w_j \sigma_i \sigma_j \rho_{i,j}}, \tag{3.17}$$

where σ_i is the annualised standard deviation (volatility) of asset i and $\rho_{i,j}$ denotes the pairwise correlation between asset i and j. According chapter 3.1.1 the weights w_i are chosen such that the volatility of each asset is set to a predetermined level, therefore $w_i = \sigma_{\text{target}}/(N \cdot \sigma_i)$. Substituting this into equation 3.17 yields:

$$\sigma_p = \sigma_{\text{target}} \sqrt{\sum_{i=1}^{N} \frac{1}{N^2} + 2 \sum_{i=1}^{N} \sum_{j=i+1}^{N} \frac{1}{N^2} \rho_{i,j}} = \frac{\sigma_{\text{target}}}{N} \sqrt{N + 2 \sum_{i=1}^{N} \sum_{j=i+1}^{N} \rho_{i,j}} \tag{3.18}$$

Since $\sum_{i=1}^{N} \sum_{j=i+1}^{N} \rho_{i,j}$ is the sum of the upper triangle entries of the correlation matrix and its number of elements is $N(N-1)/2$, the average pairwise correlation can be calculated as:

$$\bar{\rho} = 2 \frac{\sum_{i=1}^{N} \sum_{j=i+1}^{N} \rho_{i,j}}{N(N-1)}. \tag{3.19}$$

[16]To simplify the notation the formula abstracts for the moment from time. σ_p is calculated for any point in time t and σ_i and $\rho_{i,j}$ are calculated over a certain lookback period.

Using this, equation 3.18 simplifies to:

$$\sigma_p = \sigma_{\text{target}} \sqrt{\frac{1 + (N-1)\bar{\rho}}{N}}. \tag{3.20}$$

From this equation one can see how diversification benefits work on a portfolio level. From $\bar{\rho} \leq 1$ it follows that $\sqrt{\frac{1+(N-1)\bar{\rho}}{N}} \leq 1$ and therefore $\sigma_p \leq \sigma_{\text{target}}$ (remember σ_{target} is the single asset target volatility). Whenever cross asset correlation increases, the portfolio volatility increases as well and diversification benefits decrease. Equation 3.20 can be rearranged to

$$\sigma_{\text{target}} = \sigma_p \sqrt{\frac{N}{1 + (N-1)\bar{\rho}}} \tag{3.21}$$

σ_p can be substituted by $\sigma_{p,\text{target}}$, the portfolio target volatility. The average pairwise correlation $\bar{\rho}$ is then used to control the single asset target volatility level σ_{target} to decrease the exposure whenever $\bar{\rho}$ is high and vice versa, while simultaneously targeting the overall portfolio volatility level $\sigma_{p,\text{target}}$:

$$\sigma_{\text{target}} = \sigma_{p,\text{target}} \sqrt{\frac{N}{1 + (N-1)\bar{\rho}}}, \tag{3.22}$$

Including this into the time series momentum strategy defined in equation 3.5, one gets the correlation adjusted time series momentum strategy (CATSMOM):

$$r^{\text{CATSMOM}}(t, t+k) = \frac{1}{N_t} \sum_{i=1}^{N_t} \text{SIGN}_{i,t} \cdot \frac{\sigma_{p,\text{target}}}{\sigma_{i,t}} \cdot \sqrt{\frac{N_t}{1 + (N_t - 1)\bar{\rho}_t}} \cdot r_i(t, t+k) \tag{3.23}$$

$r^{\text{CATSMOM}}(t, t+k)$ is the correlation adjusted return from time series momentum over the holding period t to $t+k$. N_t is the number of assets traded at each time t, $\text{SIGN}_{i,t}$ is the SIGN trading rule as defined in equation 3.2 and $\sigma_{i,t}$ is the single asset ex-ante volatility of asset i at time t as defined in appendix A. The portfolio volatility target is set equal to 12% in accordance with Baltas & Kosowski (2014) and due to the same reasons the single asset target volatility of the standard time series momentum formula from equation 3.5 is set to 40% (see chapter 3.1.1). $\bar{\rho}_t$ is the average pairwise correlation calculated as in equation 3.19 and $r_i(t, t+k)$ is the return of asset i between t and $t+k$.

The correlation adjusted time series momentum strategy has the advantage that the portfolio volatility target $\sigma_{p,\text{target}}$ can be controlled instead of the more complicated approach of controlling the single asset target volatility σ_{target}. σ_{target} has only limited control over the ex-post portfolio volatility. Using $\sigma_{p,\text{target}}$ on the other hand is a more direct approach and it should be a much better way to stabilize the ex-post portfolio volatility. The exposure to the single assets will be reduced whenever the average pairwise correlation increases to keep the overall portfolio volatility more stable. In chapter 6.4 I will implement the formula and show, whether it improves the performance of time series momentum strategy and whether the ex-post volatility is more stable than when targeting the single asset volatility.

4. Data description and summary

The dataset I use is very similar to the dataset used by Baltas & Kosowski (2013). It consists of daily open, high, low and closing prices as well as daily volume of 71 futures contracts: 26 commodity futures, 23 equity index futures, 7 currency futures and 15 fixed income futures. In contrast to Baltas & Kosowski (2013), who obtain their futures data from Tick Data, I download my data from Datastream. To backfill equity index data I use Global Financial Data as source for equity index spot prices.[17] The earliest date available in the dataset is January 1949 for equity index data. The latest available date is 30th June 2015 and therefore I use almost three and a half years more data in comparison with Baltas & Kosowski (2013), whose last available date is 31st January 2012. The time series for the NYSE Composite contract (September 2011), Municipal Bond contract (March 2006) and Pork Bellies contract (July 2011) end prior due to delisting. The EUR/USD contract is spliced with the DEM/USD contract prior to the introduction of the Euro and the RBOB Gasoline contract is spliced with the Unleaded Gasoline contract in November 2005.

As already mentioned in chapter 3.1, I form continuous price vectors for each asset by splicing together different futures contracts using the most liquid contract at any point in time. From the daily price vectors I calculate daily, weekly (defined as Wednesday-to-Wednesday) and monthly (end-of-month) returns for each asset to form the time series momentum strategies described in chapter 3. Table B.1 in appendix B provides summary statistics for the monthly return series of each futures contract.

Futures contracts exhibit large cross sectional variation in the return distributions especially for different asset classes. While commodity and currency futures have very diverse mean returns, all equity and bond futures exhibit positive mean returns over the whole sample period. Only two assets are platykurtic ("fat-tailed") and almost all equity futures are negatively skewed, while it is very much mixed for the rest of the futures contracts. The last column of table B.1 shows Sharpe Ratios of a simple long

[17] In concordance with Baltas & Kosowski (2013) I use spot prices to prolong the time series for equity indices due to limited availability of equity futures price data. Nearest-to-delivery equity index futures prices and spot prices are highly correlated (de Roon et al., 2000).

strategy in the futures contracts over the whole period.

The most variation can be found in the cross sectional volatility. In line with the results of Baltas & Kosowski (2013) and Moskowitz et al. (2012) currency, equity and especially commodity futures are much more volatile than fixed income futures. As mentioned in chapter 3.1.1 it is important to consider this fact when building time series momentum strategies. Hence, the futures contracts are weighted by their ex-ante volatility before aggregating them to the strategy portfolio.

Table B.2 lists the futures exchanges on which the futures from the dataset are traded.

5. Performance and characteristics

In this chapter I extend the evidence for the three time series momentum strategies from Baltas & Kosowski (2013) for daily, weekly and monthly futures returns and assess their performance after January 2012, when Baltas & Kosowski (2013) stop their analysis. Moskowitz et al. (2012), Baltas & Kosowski (2013) and Hurst et al. (2013) all find that time series momentum did not work well anymore in the years following the financial crisis of 2008. Therefore, I prolong the time series and discuss the performance for more recent data. Further, I will explain important characteristics of time series momentum returns first described in Moskowitz et al. (2012) and check, whether I can reproduce them with my time series momentum return series. The stunning performance of time series momentum and its characteristics make the strategy very interesting for money managers. In chapter 5.3 I will use the fact that many hedge funds apply the strategy to introduce a simple approach to model transaction costs. Since I am reproducing the strategies from Baltas & Kosowski (2013) with a very similar dataset, the results I get should be congruent with their results. In appendix C I discuss this matter in more detail.

5.1 Time series momentum performance

All time series momentum strategies constructed in the literature are very profitable and Sharpe Ratios are high and significant for almost all tested combinations of look-back and holding periods. The monthly strategy constructed in Baltas & Kosowski (2013) returns an average profit of 18.54% p.a. over the period January 1978 to January 2012. The weekly and daily strategies yield 15.72% and 18.44% over the same period. The Sharpe Ratios of all three strategies are above 1.2 and the maximum drawdowns of the strategies lie between −12.03% for the weekly strategy and −22.12% for the monthly strategy. Thus, they are nowhere near the sometimes disastrous cross sectional momentum crashes often exceeding 40% in only one month (Daniel & Moskowitz, 2013). Moskowitz et al. (2012) and Hurst et al. (2013) find similar results. Their strategies are similarly stable and exhibit Sharpe Ratios above 1.2.

Still, it is not clear how the performance for the three strategies in Baltas & Kosowski (2013) continues after January 2012. Hence, I reproduce the three strategies and prolong them until 30th June 2015. Figure 5.1 plots the log-performance of the daily, weekly and monthly strategies and gives a first overview. In concordance with Baltas & Kosowski (2013) I start forming the strategies in January 1978.

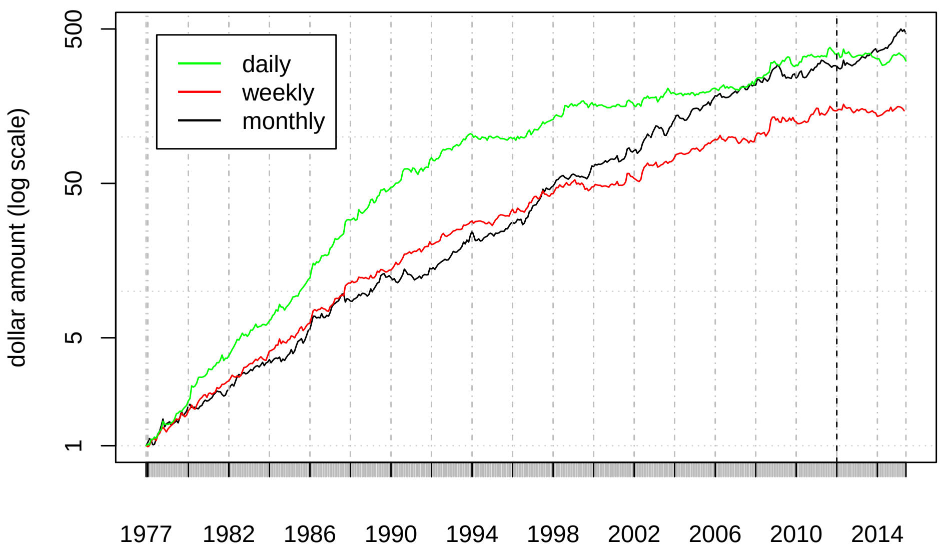

FIGURE 5.1: Dollar growth of time series momentum plotted on a log scale. The black line is the growth of 1$ in log-terms from January 1978 to June 2015 for the monthly time series momentum strategy. The red line and the green line are the dollar growth in log-terms for the weekly and daily strategies. The dashed vertical line indicates the last date used in Baltas & Kosowski (2013), which was January 2012.

It is interesting that while the daily and weekly strategies seem not to perform well anymore after the financial crisis of 2008, the monthly time series momentum strategy gained substantially in value in the last year. Table 5.1 provides some summary statistics for the overall performance and the performance between June 2009 and January 2012 as well as from February 2012 to June 2015. The first period is interesting since it is the last three years of data in the sample of Baltas & Kosowski (2013), when time series momentum seems not to perform that well anymore and the second period extends the evidence of time series momentum.[18]

[18] Another extension of time series momentum was conducted by Hurst et al. (2012), who prolong the time series used in Moskowitz et al. (2012) and Hurst et al. (2013) back to 1903. They find that trend following is consistently profitable for over 110 years. Forming the same strategies as in Hurst et al.

	daily			weekly			monthly		
	full	09-12	12-15	full	09-12	12-15	full	09-12	12-15
Mean (%)	16.49	3.58	−2.96	14.25	3.70	0.04	17.77	5.84	15.25
Volatility (%)	13.07	12.99	11.47	11.71	12.42	9.86	13.16	12.10	11.93
Skewness	1.08	0.94	0.70	0.56	−0.35	0.33	−0.15	−0.46	0.09
Kurtosis	6.40	5.35	5.54	4.77	3.15	3.93	3.42	3.13	4.58
Sharpe Ratio	1.26	0.28	−0.26	1.22	0.30	0.00	1.35	0.48	1.28
MDD (%)	23.44	13.45	21.38	16.53	9.84	16.53	18.23	9.99	8.09
$ growth	310.24	1.10	0.90	147.83	1.10	1.00	467.39	1.16	1.62

TABLE 5.1: Performance of time series momentum. This table shows a summary of the performance of the daily, weekly and monthly strategy for the full sample period, for June 2009 to January 2012 and for February 2012 to June 2015. The annualised return (mean), annualised standard deviation (volatility) and maximum drawdown are displayed in percentage terms. The Sharpe Ratio is in annualised terms. $ growth indicates the amount an investment of 1$ would have grown to over the relevant period.

Over the full sample period all three strategies provide high mean returns ranging from 17.77% for the monthly strategy to 14.25% for the weekly strategy. The Sharpe Ratios (SR) are all above 1.2 and the maximum drawdowns range from 23.44% to 16.53%. Using a target volatility σ_{target} of 40% per asset I reach an annualised volatility of around 11–13% for the whole strategy, which is in line with Moskowitz et al. (2012) and Baltas & Kosowski (2013). The skewness of the three strategies varies substantially from a strongly positive skewness of the daily strategy to a slightly negative one for the monthly strategy. The kurtosis of the strategies differ as well with the daily strategy obtaining the highest value and the monthly strategy the lowest but all being greater than 3. All results are very similar to those reported in Baltas & Kosowski (2013). Compared with the performance of the MSCI World over the same time period, which was 7.67% annually with a Sharpe Ratio of just 0.49 and a drawdown of 55.37%, all three strategies did very well.

In the period from June 2009 to January 2012 – after the financial crisis of 2008 – time series momentum seemed not to work that well anymore. Even though obtaining still positive returns, the Sharpe Ratios are close to zero (in a time period when the MSCI World gained more than 20% in value with a Sharpe Ratio of around 0.5). Hurst et al. (2012) argue that time series momentum returns after 2008 are not significantly

(2013) and aggregating them to one equally weighted portfolio they show that their strategy returned over 20% p.a. over the whole period and performed well through recessions and expansions, stagflation and wartimes as well as rising and falling interest rates regimes with Sharpe Ratios ranging from 0.53 to 1.89 per decade. Even further, the maximum drawdown experienced by their strategy over the whole sample period was only −26.3% between March 1947 and March 1954.

out of line with previous phases of lower returns and therefore they should not provide a challenge for the strategy as a whole.

More puzzling are the results for the recent time period from February 2012 to June 2015. While monthly time series momentum returns to old strengths, daily and weekly time series momentum perform flat or even negative. The correlations between the strategies however are still relatively high over that time period, compared to the correlation structure over the whole period (see table 5.2) even if the correlations for this period are not monotone anymore. On the other hand, the correlations between the different strategies decreased substantially in the period after the financial crisis. This is particularly interesting due to the fact that the average pairwise correlation between the single assets increased in the aftermath of the financial crisis. I will come back to this in chapter 6.4.

	full			**09-12**			**12-15**		
	D	W	M	D	W	M	D	W	M
D	1.00	0.55	0.21	1.00	0.28	−0.18	1.00	0.44	0.55
W	0.55	1.00	0.41	0.28	1.00	0.24	0.44	1.00	0.47
M	0.21	0.41	1.00	−0.18	0.24	1.00	0.55	0.47	1.00

TABLE 5.2: Correlation matrix for time series momentum. Displayed are the correlation matrices over the full sample period, the period between June 2009 and January 2012 and between February 2012 and June 2015 for the daily (D), weekly (W) and monthly (M) strategies. The full sample period is from January 1978 to June 2015.

Table 5.2 also shows that correlations between different time series momentum strategies are not as high as their similar construction method might suggest. Hurst et al. (2013) find for instance that the performance can be increased when combining strategies of different lookback periods. By combining their 12 month, 3 month and 1 month lookback period and 1 week holding period strategies to an equally weighted portfolio, they are able to achieve a Sharpe Ratio of 1.8. If I construct an equally weighted portfolio from the daily, weekly and monthly time series momentum strategies over the whole sample period I get a mean return of 16.52% with a volatility of 9.7% and a Sharpe Ratio of 1.7. An unreported subsample analysis with the same subsamples as in appendix D shows that the outperformance of the combined strategy decreases over time. It is particularly high in period 1 (January 1978 to December 1987) with a Sharpe Ratio of 3.3 but from period 3 onwards (after January 1998) the monthly strategy is superior.

	MSCI World Index		
	full	09-12	12-15
D	-0.15	-0.29	-0.39
W	-0.11	-0.02	-0.25
M	0.12	0.46	-0.13

TABLE 5.3: Market correlation of time series momentum. The table shows the correlation of daily (D), weekly (W) and monthly (M) time series momentum with the monthly MSCI World Index returns over the full sample period, the period between June 2009 and January 2012 and between February 2012 and June 2015. `https://www.msci.com/end-of-day-data-search` (access date: 2016-02-29) provides daily, monthly and yearly price data for all MSCI indices. I use monthly USD end-of-day prices to calculate monthly returns. The full sample period is from January 1978 to June 2015.

Time series momentum strategy returns are mostly not or negatively correlated with market returns. In table 5.3 I calculate the correlations of daily, weekly and monthly time series momentum returns with monthly MSCI World Index returns. It is interesting that the correlation between monthly time series momentum and the MSCI World reaches 46% for the period between June 2009 and January 2012 when it did not perform well, but is close to zero (but positive) over the full period and negative from February 2012 to June 2015. The daily and weekly strategies on the other hand show a negative correlation with the market over the full period and in both subperiods.

It seems that the volatility weighting parameter is very important for the performance of the strategy. A simpler strategy without the weighting scheme (see equation 3.1) yields only 5.48% (SR: 0.87), 4.97% (SR: 0.84) and 5.9% (SR: 0.96) for the daily, weekly and monthly strategy. By weighting the returns with their ex-ante volatilities the exposure to high risk assets is reduced, which does not only increase the risk adjusted return (as measured by the Sharpe Ratio), but also the absolute performance is substantially higher.

5.2 Characteristics of time series momentum

Moskowitz et al. (2012), Baltas & Kosowski (2013) and Hurst et al. (2013) build a variety of time series momentum strategies using equation 3.6 and find some common return characteristics, that make the strategy particularly interesting for asset managers. In the following analysis I will present their results and add further evidence conducting similar tests with my own return series.

5.2.1 Risk factor loadings of time series momentum

Not only are time series momentum returns very impressive and drawdowns very small, they are also highly unrelated to other risk factors. Moskowitz et al. (2012) regress a variety of time series momentum strategies with different lookback and holding periods on a market index, a bond index, a commodity index as well as the Fama-French (1993) factors SMB and HML, representing size and value, and the Carhart (1997) cross sectional momentum factor UMD ("up minus down"). They find that the alphas of the strategies are all positive and almost all significant for lookback and holding periods shorter than a year, not only for the aggregate strategies but also for the single asset class strategies. Baltas & Kosowski (2013) confirm these results in a subsample analysis.

The only beta coefficient that is significant and positive is of UMD, which is not surprising due to its relatedness, even if this cross sectional momentum factor catches only stock momentum. Still, they find that time series momentum cannot be fully explained by cross sectional momentum due to its highly significant alpha. As a further test, Moskowitz et al. (2012) regress the monthly strategy on the Asness et al. (2012) value and momentum factors, since those are diversified over all asset classes and therefore more related. The loading on the momentum factor is now highly significant but still the strategy generates an alpha of around 1% per year.

Table 5.4 provides a similar regression of my time series momentum strategy returns on a market factor, SMB, HML and UMD factor, all provided in the Kenneth R. French data library.[19]

I get very similar results as Baltas & Kosowski (2013). All three strategies provide highly significant alphas ranging from 14.45% to 20.24% in annualised terms. While for

[19] `http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html` (access date: 2016-02-29) provides the data and further details on how the factors are constructed. The market factor is represented by the excess returns above the 1 month T-bill of a value-weighted portfolio of all firms in the CRSP database incorporated in the US. SMB is the size factor, HML is the value factor and UMD is a equity cross sectional momentum factor. Note that the UMD factor is called MOM on the website.

	daily	weekly	monthly
Intercept	0.015480***	0.011854***	0.011312***
	(6.422629)	(7.338947)	(6.577479)
Mkt-Rf	−0.001833*	−0.000640	0.001416
	(−2.492510)	(−0.960854)	(1.788482)
SMB	−0.000871	−0.000969	−0.000472
	(−1.032441)	(−1.558218)	(−0.748275)
HML	−0.000921	−0.000104	0.000773
	(−1.015338)	(−0.185870)	(1.079992)
UMD	−0.000553	0.000814*	0.003262***
	(−1.350132)	(2.233947)	(6.791512)
R^2 (%)	5.27	3.02	15.01
adj. R^2 (%)	4.42	2.14	14.24
Num. obs.	450	450	450

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

TABLE 5.4: Factor loadings of time series momentum returns. The daily, weekly and monthly time series momentum strategies are regressed on risk factors provided in Kenneth R. French's data library (`http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html` (access date: 2016-02-29)). Newey & West (1987) t-statistics are reported in brackets underneath the regression coefficients. Mkt-Rf represents the market factor minus the risk free rate and is constructed via a value-weighted portfolio of all firms in the CRSP database incorporated in the US minus the 1 month T-bill rate. SMB is the size factor, HML is the value factor and UMD is a cross sectional equity momentum factor. The sample period is January 1978 to June 2015.

daily returns only the market factor is slightly significant (with a negative coefficient), the cross sectional momentum factor is significant only for time series momentum of higher periods. UMD is highly significant for the monthly strategy but the alpha is still very high.

Moskowitz et al. (2012) look further into the relationship between cross sectional momentum and time series momentum. To make them comparable they form a standard cross sectional momentum strategy in the style of Asness et al. (2012). A regression of time series momentum on cross sectional momentum produces a beta of 0.66 with an R^2 of 44%, still leaving a highly significant alpha of around 76 basis points per month. If cross sectional momentum is regressed on time series momentum on the other hand, the intercept turns negative and insignificant. Further, Moskowitz et al. (2012) decompose cross sectional momentum returns into three components, an auto-covariance term, a cross-covariance component and a cross-sectional variation in unconditional mean returns and time series momentum returns into two components, an auto-covariance term and an average squared mean excess return following the methodology of Lewellen (2002).[20] Like this, cross sectional momentum and time series momentum returns can be easily linked by looking at the contributions of the single components to each factor's returns. The results obtained by the analysis are shown in table 5.5. Both strategies load similarly positive on the auto-covariance component, which is the return contribution of the relationship between the past 12 month return and the future 1 month return. This factor is the main driver for cross sectional momentum and time series momentum returns. The cross-sectional variation in unconditional mean returns and the average squared mean excess return load also slightly positive on both strategies, but the component for time series momentum is stronger. The cross-covariance component from cross sectional momentum on the other hand, which covers the cross sectional relationship between past returns and future returns, contributes negatively to cross sectional momentum returns. Like this, it is possible to explain why time series momentum (TSMOM) performs better than cross sectional momentum (CSMOM).

TSMOM		**CSMOM**	
factor	loading	factor	loading
auto-covariance term	0.54%	auto-covariance term	0.53%
average squared mean excess return	0.29%	cross-sectional variation in unconditional mean returns	0.12%
		cross-covariance component	-0.03%

TABLE 5.5: Strategy decomposition. Time series momentum returns can be decomposed into two components, an auto-covariance term and an average squared mean excess return. Cross sectional momentum returns can be decomposed into three components, an auto-covariance term, a cross-covariance component and a cross-sectional variation in unconditional mean returns. The monthly loadings are in percentage terms and from panel B of table 5 in Moskowitz et al. (2012).

As a further check of the relationship between time series momentum and cross sectional momentum I construct a cross sectional momentum strategy from my dataset using equation 3.6, but with $\text{CSMOM}_{i,t}$ as trading rule instead of $\text{SIGN}_{i,t}$:

$$\text{CSMOM}_{i,t} = \begin{cases} +1 & \text{if } r_i(t-j,t) \in Q_{\text{top}} \\ -1 & \text{if } r_i(t-j,t) \in Q_{\text{bottom}} \end{cases} \tag{5.1}$$

[20]The analysis is conducted for a monthly time series momentum strategy only.

where Q_{top} are the 20% top performer and Q_{bottom} are the 20% worst performer over the time period $t - j$ to t. For simplicity I restrict my analysis to monthly returns only.

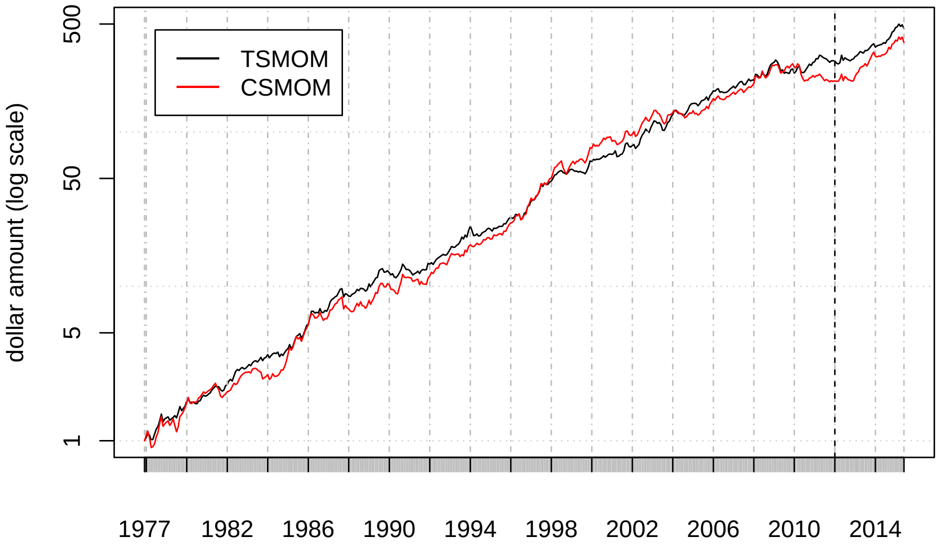

FIGURE 5.2: Time series momentum versus cross sectional momentum. Dollar growth of a monthly time series momentum strategy and cross sectional momentum strategy plotted on a log scale. The black line is the growth of 1$ in log-terms from January 1978 to June 2015 for the monthly time series momentum strategy. The red line is the dollar growth in log-terms for the monthly cross sectional momentum strategy.

Figure 5.2 plots the log-performance of both strategies and it already indicates that time series momentum does not only perform better than cross sectional momentum, but it is also more robust to crashes. The left panel of table 5.6 reports a few summary statistics for cross sectional momentum and for time series momentum (similar to table 5.1). Cross sectional momentum has a similar mean return but higher volatility, thus obtains a lower Sharpe Ratio. The maximum drawdown is also higher than for time series momentum. Interstingly, cross sectional momentum is "fat-tailed" while time series momentum is leptokurtic.

The right panel of table 5.6 shows two regressions. In the left column I regress cross sectional momentum returns on time series momentum returns. In line with Moskowitz et al. (2012) I find that cross sectional momentum is well explained by time series momentum and the alpha is not significant anymore. Time series momentum on the other hand still has a significant alpha of 6.16% p.a. even if the beta coefficient of

	CSMOM	TSMOM
Mean (%)	17.12	17.77
Volatility (%)	15.95	13.16
Skewness	−0.27	−0.15
Kurtosis	0.68	3.42
Sharpe Ratio	1.07	1.35
MDD (%)	23.70	18.23
$ growth	379.39	467.39

	CSMOM	TSMOM
Intercept	0.000303	0.004995***
	(0.183106)	(4.078184)
TSMOM	0.970184***	
	(20.587665)	
CSMOM		0.660659***
		(22.601543)
R^2 (%)	46.11	46.11
adj. R^2 (%)	45.99	45.99
Num. obs.	450	450

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

TABLE 5.6: Time series momentum versus cross sectional momentum. The left panel reports summary statistics for the monthly cross sectional momentum strategy and monthly time series momentum strategy from January 1978 to June 2015. The annualised return (mean), annualised standard deviation (volatility) and maximum drawdown are displayed in percentage terms. The Sharpe Ratio is in annualised terms. $ growth indicates the amount an investment of 1$ would have grown to over the whole period. The right panel shows in the left column a regression of cross sectional momentum on time series momentum and in the right column a regression of time series momentum on cross sectional momentum. Newey & West (1987) t-statistics are reported in brackets underneath the regression coefficients.

cross sectional momentum is highly significant. This indicates that time series momentum is superior to cross sectional momentum since it not only captures cross sectional momentum very well but also produces a significant positive alpha.

5.2.2 The time series momentum smile

The most prominent characteristic of time series momentum is its good performance in turbulent market phases. Hurst et al. (2012) find that in times a classic 60/40 portfolio[21] exhibited its worst drawdowns (over the period 1903–2012), time series momentum always but once performed positively and in most cases gaining more than 25% in value. Especially in 2008 the strategy was very lucrative and while the stock market lost around 30% of its value, time series momentum performed very well over the same period. This can be explained due to the often gradual occurence of such bear markets. After some small losses, time series momentum strategies position investors correctly to gain from a further decrease in the price of the underlying assets.

Time series momentum needs clear trends to perform well. Its payoffs are therefore usually higher whenever markets are turbulent, either on the downside or upside.

[21] The 60/40 portfolio from Hurst et al. (2012) invests 60% in the S&P 500 equity index and 40% in US 10 year bonds.

Plotting time series momentum returns against stock market returns gives therefore rise to a smile pattern. This is also why time series momentum returns are similar to straddle based strategies (Moskowitz et al., 2012). On the other hand, when markets are stagnating, time series momentum strategies are not working well. This happend for instance after the recent crisis. When trends are absent, time series momentum performance is flat or even negative. Figure 5.3 plots the returns of the three time series momentum strategies against the returns of the MSCI World index. The blue line is a fitted quadratic least squares model. I find that daily and weekly time series momentum returns show the smile pattern discovered by Moskowitz et al. (2012), while the monthly returns from my strategy do not display the same pattern.

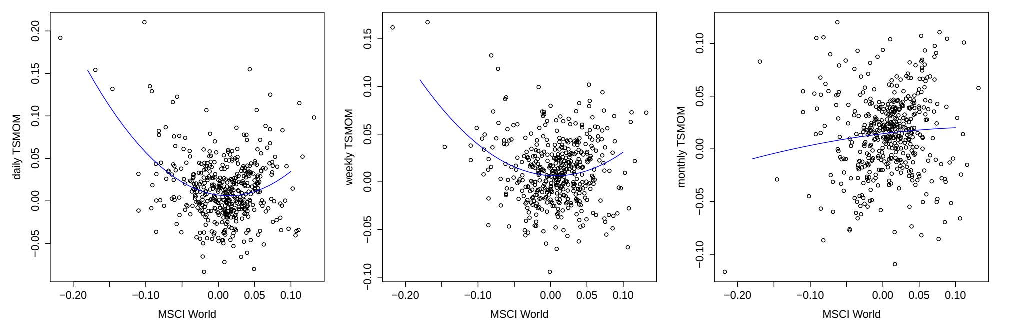

FIGURE 5.3: Time series momentum smile. The figure shows scatterplots of daily, weekly and monthly time series momentum returns against the return of the MSCI World index from January 1978 to June 2015. The blue lines fit a quadratic least squares model.

The regression summary in table 5.7 supports these results. The beta coefficients of daily and weekly time series momentum returns are highly significant for squared MSCI World returns. This implies that both are a good hedge against strong market movements in either direction. As expected, none of the three strategy return series can be explained by the market returns and all exhibit high and significant alphas. Especially for monthly time series momentum the model seems not to be a good fit due to the very low R^2 and high alpha. In contrast to Moskowitz et al. (2012) and Baltas & Kosowski (2013) I find no evidence that monthly time series momentum is a good hedge against tail events. Unreported tests with the Mkt-Rf factor from table 5.4 and the S&P 500 index returns confirm these results.

	daily	weekly	monthly
Intercept	0.005163^{**}	0.005575^{**}	0.013306^{***}
	(2.597577)	(3.246513)	(6.620530)
MSCI World	-0.064699	-0.035947	0.105970
	(-1.106152)	(-0.677928)	(1.007283)
(MSCI World)^2	4.705714^{***}	3.417683^{***}	0.219493
	(6.120742)	(5.729316)	(0.217393)
R^2 (%)	19.02	12.23	1.37
adj. R^2 (%)	18.66	11.83	0.93
Num. obs.	450	450	450

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

TABLE 5.7: Time series momentum smile. Daily, weekly and monthly time series momentum returns on monthly basis are regressed on MSCI World returns and squared returns. Newey & West (1987) t-statistics are reported in brackets underneath the regression coefficients.

5.3 Hedge fund returns and transaction costs

Time series momentum returns are able to explain the long time mysterious hedge fund returns from CTAs or Managed Futures Funds that exhibit significant alpha if regressed on classical risk factors. Fung & Hsieh (2001) are the first to explain hedge fund alphas by building lookback straddle factors[22], but time series momentum strategies offer some advantages over such strategies. First, they are a more direct approach to proxy hedge fund returns and can be applied in practice by trend following funds. Second, Baltas & Kosowski (2013) show that when adding their monthly, weekly and daily time series momentum benchmarks to the Fung & Hsieh (2004) model for hedge fund returns, the explanatory power is increased and the significance of some of the straddle factors is driven out. Baltas & Kosowski (2013) and Hurst et al. (2013) find strong evidence that hedge funds engage in time series momentum strategies of various time frames.

One way to proxy trading costs for time series momentum strategies in a very conservative way is therefore to assume an annual 2% management fee and 20% performance fee subject to a high watermark (also called 2/20 fee structure), as it is usually charged by hedge funds. After accounting for transaction costs Hurst et al. (2013) still

[22]A lookback straddle is an option strategy which consists of a lookback call option and a lookback put option. The lookback call option grants its holder the right to buy an asset for the lowest price observed over the lifetime of the option while the lookback put option grants the right to sell the asset for the highest price observed.

find a Sharpe Ratio of 1 for their aggregate portfolio and Baltas & Kosowski (2013) find that the average returns are reduced to 13.22% for the monthly strategy, 11.12% for the weekly strategy and 13.46% for the daily strategy. The Sharpe Ratios are reduced to slightly below 0.9 for all three strategies, which is still very impressive.

Assuming a 2/20 fee structure brings trading costs to an average of 6% per year. Hurst et al. (2012) estimate transaction costs starting in 1903 and find that they are substantially lower now than decades ago due to increased trading volume and price competition. Hurst et al. (2013) believe that sophisticated managers can bring transaction costs down to 1–4% per year.

	daily	weekly	monthly
Mean (%)	10.43	8.65	11.12
Volatility (%)	11.48	10.43	11.83
Skewness	0.69	0.21	−0.47
Kurtosis	2.34	1.16	0.60
Sharpe Ratio	0.91	0.83	0.94
MDD (%)	27.29	19.27	19.48
$ growth	41.69	22.43	52.53

TABLE 5.8: Time series momentum with transaction costs. The table reports summary statistics for the daily, weekly and monthly time series momentum strategies assuming a 2/20 fee structure. At each end of month a proportional monthly share of the 2% annual management fee and a 20% performance fee subject to a high watermark is substracted. The annualised return (mean), annualised standard deviation (volatility) and maximum drawdown are displayed in percentage terms. The Sharpe Ratio is in annualised terms. $ growth indicates the amount an investment of 1$ would have grown to over the relevant period. The sample period is from January 1978 to June 2015.

Table 5.8 reports the summary statistics for my daily, weekly and monthly time series momentum strategies if a 2/20 fee structure is applied on monthly basis. The strategies are still very lucrative, even if Sharpe Ratios are reduced to under 1 for all three strategies.

6. Improving time series momentum

In this chapter I implement the extensions for time series momentum strategies that are introduced in chapter 3.2. Baltas & Kosowski (2012) and Marshall et al. (2014) propose different time series momentum signals to increase the performance of the strategy. Baltas & Kosowski (2012) find that by using a significant trend rule (TREND) instead of the SIGN rule, the turnover of the strategy can be reduced significantly but risk adjusted return is almost unaffected. Marshall et al. (2014) on the other hand implement a moving average rule (MAR) and argue that it gives an earlier and therefore better signal than the simple SIGN rule.

In chapter 5 I showed that time series momentum strategies are very profitable over a long period of time, but in more recent years and especially after the financial crisis of 2008 they performed not so well anymore. Baltas & Kosowski (2014) find that the performance of time series momentum stagnates whenever diversification benefits decrease. To adress this issue, they add an average pairwise correlation factor to the weighting scheme of time series momentum strategies. This reduces the exposure to the strategy when asset prices are highly correlated.

To implement the various extensions I use the dataset which I presented in chapter 4 starting in January 1978 and ending in June 2015. For reasons of better readability and due to the fact that it is the most prominent strategy in the literature, I will focus my analysis only on the monthly time series momentum strategy. The lookback period used to construct the SIGN rule, as well as for the construction of the moving average necessary for the MAR rule is 12 months. The average pairwise correlation factor is measured over a period of 60 days in concordance with Baltas & Kosowski (2014). The single asset volatility target is set to 40% as in the previous chapter and the portfolio volatility target used in chapter 6.4 is set to 12%.

6.1 Turnover dynamics

Before implementing the extensions mentioned above I want to introduce a new measure that is helpful in comparing different time series momentum strategies and is also used in Baltas & Kosowski (2014). A very important aspect of asset management are transaction costs and therefore turnover plays an important role for determining if a strategy is feasible or not and whether one strategy is superior to another by decreasing the turnover and therefore increasing the net performance. The average annual portfolio turnover for the monthly strategy is calculated as following:

$$\text{turnover} = \frac{\text{total purchases}}{\text{number of average portfolio holdings}} \cdot \frac{12}{\text{number of total months}} \tag{6.1}$$

In my sample the number of total months is equal to 450. The number of average portfolio holdings is the average number of all absolute monthly portfolio holdings (long and short). The total purchases are defined as the sum of all absolute differences in the weights over all time periods t and assets i. For the standard time series momentum strategy with the SIGN signal this is equal to

$$\text{total purchases}_{\text{SIGN}} = \sum_{t=1}^{T} \sum_{i=1}^{N_t} \left(\frac{\text{SIGN}_{i,t+1}}{\sigma_{i,t+1}} - \frac{\text{SIGN}_{i,t}}{\sigma_{i,t}} \right), \tag{6.2}$$

where T is the number of total months and N_t is the number of assets traded in period t. $\text{SIGN}_{i,t}$ is defined as in equation 3.2. The total purchases of the TREND signal and MAR signal are defined similarly but by replacing $\text{SIGN}_{i,t}$ with the trading rules $\text{TREND}_{i,t}$ and $\text{MAR}_{i,t}$ (see equation 3.11 and equation 3.13).

The turnover of the correlation adjusted time series momentum strategy can be defined in the same manner but the total purchases are then given by

$$\text{total purchases}_{\text{CATSMOM}} = \sum_{t=1}^{T} \sum_{i=1}^{N_t} \left(\frac{\text{SIGN}_{i,t+1}}{\sigma_{i,t+1}} z_{t+1} - \frac{\text{SIGN}_{i,t}}{\sigma_{i,t}} z_t \right), \tag{6.3}$$

with the signal $\text{SIGN}_{i,t}$ from equation 3.2. z_t is defined as

$$z_t = \sqrt{\frac{N_t}{1 + (N_t - 1)\bar{\rho}_t}}, \tag{6.4}$$

where $\bar{\rho}_t$ is the average pairwise correlation at time t, which is defined in equation 3.19.

The average annual portfolio turnover is a measure of how much of the total purchases are traded on average over a whole year relative to the number of average portfolio holdings. The higher the turnover, the higher are usually the transaction costs. This relationship must not always hold though, since trading costs do also depend on the volume per transaction, the agreement between broker and asset manager or the bid/ask spread of the particular asset. The simple measure of average annual portfolio turnover I use here abstracts from all those factors, but since I only compare similarly constructed trading strategies, all this other influences should somewhat even out.

There are two factors affecting the turnover for the SIGN, TREND and MAR trading rules, i.e. the change in ex-ante volatility $\sigma_{i,t}$ and the change in the trading signal $\text{SIGN}_{i,t}$, $\text{TREND}_{i,t}$ or $\text{MAR}_{i,t}$. While the ex-ante volatility weighting scheme improves the performance of time series momentum as mentioned in chapter 5.1, it also strongly increases the strategy turnover. The change from $+1$ to -1 and vice versa of the trading signal has by definition an effect of 2 on portfolio turnover. The correlation adjusted time series momentum strategy has an additional factor z_t that influences portfolio turnover. Whenever average pairwise correlation increases among the assets, the exposure to all futures contracts is reduced. Note that the constant factor in the weighting scheme of the strategies constructed in chapter 3, $\frac{\sigma_{\text{target}}}{N_t}$ or $\frac{\sigma_{p,\text{target}}}{N_t}$, is eliminated by dividing the total purchases with the number of average portfolio holdings (see equation 3.5).

The average annual portfolio turnover is defined relative to the average monthly portfolio holdings of the strategy. Therefore, if two strategies have the same average annual portfolio turnover, but one of the two has less total purchases and a lower number of average monthly portfolio holdings, this strategy is clearly more favorable than the other, since trading costs should be smaller as well. To account for this, I will also report the number of average monthly portfolio holdings when comparing different strategies in the following sections.

Annual turnover is in general quite high for time series momentum strategies. For the standard monthly time series momentum strategy (using SIGN as the trading signal) I get an average annual portfolio turnover of 339.78%. This is not only due to the volatility weighting scheme. A strategy that does not scale the positions by their ex-ante volatility still produces an annual turnover of 233.85%.

6.2 Implementing a significant TREND trading signal

Baltas & Kosowski (2012) propose a more sophisticated trading rule than the simple SIGN signal from equation 3.2. They find that time series momentum is profitable whenever prices are trending but does not work well when clear trends are missing. To adress this issue they introduce a significant trend trading rule, that only invests whenever prices exhibit a significant trend and does not invest, when this is not the case. From equation 3.11 one can see that Newey & West (1987) t-statistics of greater than $+2$ or smaller than -2 are needed to trigger a buy or sell signal for the asset, which means that the trend should be significant at approximately the 95% level.

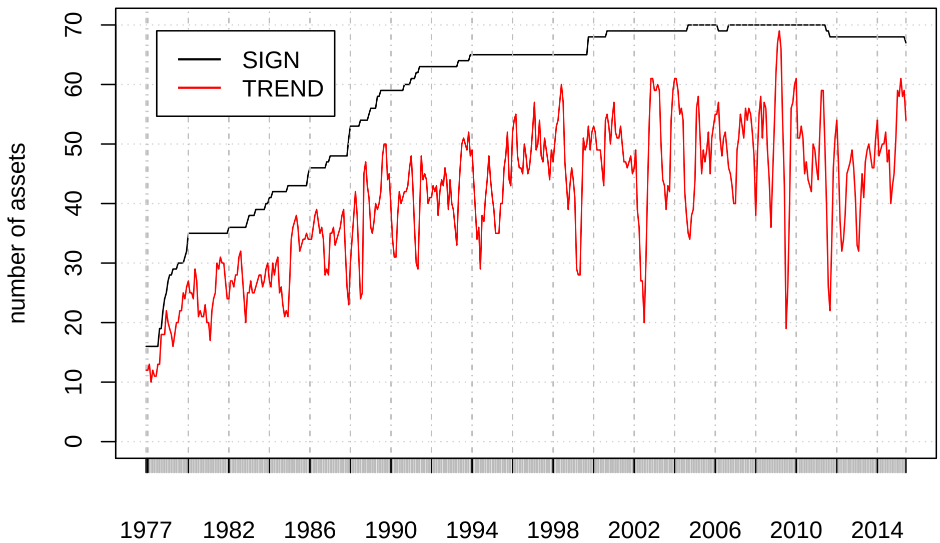

FIGURE 6.1: Number of traded contracts for SIGN and TREND signal. The black line represents the number of assets the SIGN signal trades at any point in time. By construction it is always equal to the number of all available assets. The red line shows the number of assets the TREND signal trades.

Figure 6.1 plots the number of held assets in the portfolio for the SIGN signal and

TREND signal. The SIGN signal is always invested in all contracts available by construction, while the TREND signal does only invest in assets whose price trend is statistically significant. The figure shows that the TREND signal is much less active in some periods.

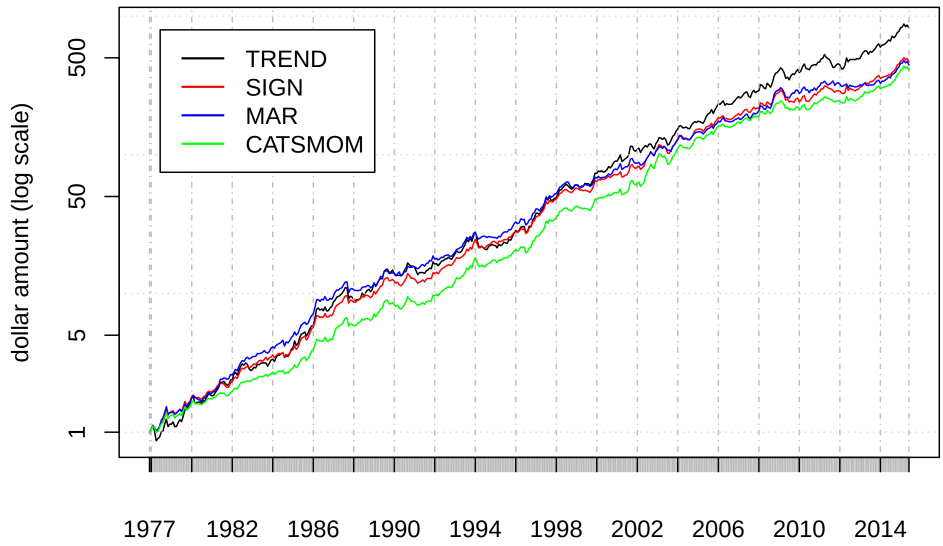

FIGURE 6.2: Performance comparison of different time series momentum strategies plotted on a log scale. The black strategy uses the TREND signal, the red strategy the SIGN signal, the blue strategy the MAR signal and the green line represents the correlation adjusted time series momentum strategy (CATSMOM). The plot shows the return of 1$ in log-terms over the period January 1978 to June 2015 for all four strategies.

Figure 6.2 plots the log-performance of the strategy using the TREND signal in comparison with the strategy using the SIGN signal. It seems that the TREND signal is able to improve the return of time series momentum. Table 6.1 shows that the mean return can be increased to almost 20% if the TREND signal is used instead of the SIGN signal. The risk adjusted return on the other hand is slightly lower due to the increase in volatility and the maximum drawdown experienced over the whole sample period is also bigger. It seems that the TREND signal makes the strategy more lucrative because it excludes assets that do not exhibit a clear price trend but this in turn decreases the diversification among assets and therefore increases risk. The annualised turnover is also lower for the TREND signal and the average portfolio holdings are reduced by almost 30% compared to the time series momentum strategy using the SIGN signal.

When restricting my sample period until January 2012 I get similar results as Baltas & Kosowski (2012). As mentioned in chapter 3.2.1 they find that the Sharpe Ratios are very similar for both strategies but portfolio turnover is significantly reduced. It seems that the TREND rule performs especially well in the last couple of years. The subsample analysis in appendix D confirms these results.

	SIGN	TREND	MAR	CATSMOM
Mean (%)	17.77	19.54	17.60	17.35
Volatility (%)	13.16	16.31	13.37	12.86
Skewness	−0.15	−0.26	−0.18	−0.05
Kurtosis	3.42	3.78	4.33	3.78
Sharpe Ratio	1.35	1.20	1.32	1.35
MDD (%)	18.23	24.86	16.24	15.81
$ growth	467.39	818.72	443.36	408.84
turnover (%)	339.78	327.30	402.41	529.76
avg. holdings	650.14	467.25	651.48	716.52

TABLE 6.1: Summary statistics for time series momentum extensions. This table shows a summary of the performance of the monthly time series momentum strategy when using the SIGN signal, TREND signal, MAR signal and correlation adjusted time series momentum (CATSMOM) from January 1978 to June 2015. The annualised return (mean), annualised standard deviation (volatility) and maximum drawdown are displayed in percentage terms. The Sharpe Ratio is in annualised terms. $ growth indicates the amount an investment of 1$ would have grown to over the full period. The turnover is annualised and in percentage terms (see chapter 6.1 for the definition) and the average holdings are the monthly average holdings summed over all assets in absolute terms (long and short).

6.3 Implementing a moving average MAR trading signal

Marshall et al. (2014) propose to use a moving average trading rule (MAR) instead of the SIGN rule from Moskowitz et al. (2012), Baltas & Kosowski (2013) and Hurst et al. (2013). They argue that moving averages give better and earlier signals and therefore are able to increase returns of time series momentum strategies. In chapter 3.2.1 I show that the SIGN signal coincides with MA direction changes, but the MAR signal only requires the price to go above or below the MA to give a buy or sell signal, which makes the MAR in theory a better signal. In contrast, table 6.1 reveals that the summary statistics of the MAR rule are very similar to the ones produced by the SIGN rule. The major difference is that turnover is higher for the MAR signal, making it more expensive to pursue.

The results indicate that the price moves much more often above or below the MA than a MA direction change takes place, causing the sign to switch too often from positive to negative and vice versa and therefore causing unnecessary turnover. This is also confirmed in appendix D. The MAR trading rule adds no additional value to time series momentum. It performs very similar but has a higher turnover in all subsamples considered.

6.4 Implementing pairwise correlation

As a last extension, Baltas & Kosowski (2014) introduce an average pairwise correlation factor to the weighting scheme of time series momentum strategies.[23] They argue that time series momentum does not perform well whenever the correlation among all assets in their sample increases.

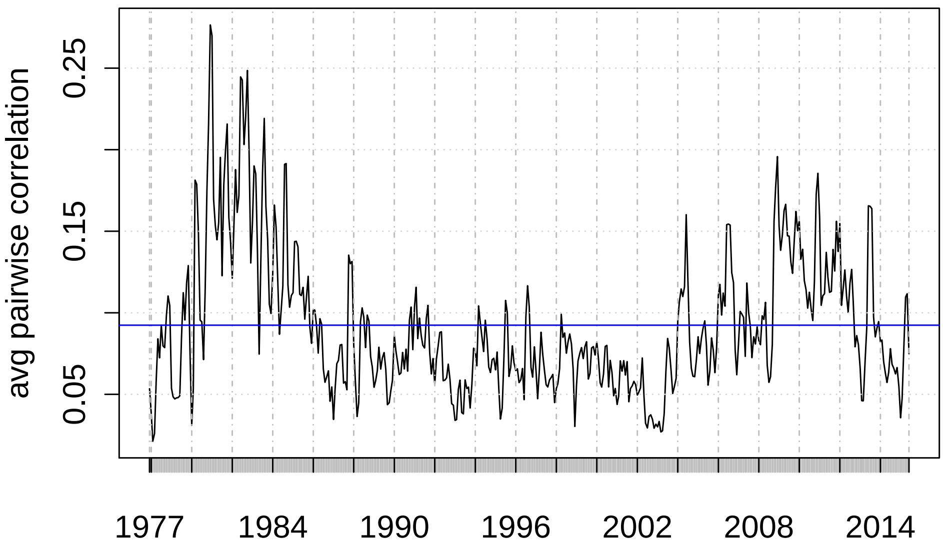

FIGURE 6.3: Average pairwise correlation. The figure plots the average pairwise correlation factor calculated as in equation 3.19 with $\rho_{i,j}$ measured over a period of 60 days for all assets where data exists at each point in time. The blue horizontal line is the ex-post mean which is equal to 0.0924. The sample period is January 1978 to June 2015.

Figure 6.3 shows the average pairwise correlation over the whole sample period from January 1978 to June 2015. It can be seen that especially in the late 1970s and

[23] Equation 3.19 shows how to calculate the average pairwise correlation factor.

	TSMOM
Intercept	0.023970^{***}
	(5.845859)
avg. pairwise correlation	-0.103174^{*}
	(-2.530267)
R^2 (%)	1.4
adj. R^2 (%)	1.18
Num. obs.	450

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

TABLE 6.2: Average pairwise correlation and time series momentum returns. Monthly time series momentum returns using the SIGN signal are regressed on the average pairwise correlation factor calculated as in equation 3.19. $\rho_{i,j}$ is measured over a period of 60 days for all assets where data exists at each point in time. Newey & West (1987) t-statistics are reported in brackets underneath the regression coefficients. See appendix E for a discussion of the methodology. The sample period is January 1978 to June 2015.

beginning of the 1980s as well as after the crisis of 2008 the pairwise correlation is above the ex-post average, represented by the blue horizontal line. However, the high average pairwise correlation at the beginning of the time series should be observed with caution due to only limited data availability (see Appendix B) and higher correlation might paricularly stem from the fact that one third of the available futures contracts at that time are currency futures.

To check whether correlation among contracts has a significant influence on time series momentum, I regress monthly time series momentum returns on the average pairwise correlation factor. Table 6.2 shows that the coefficient is significant at the 5% level and negative, indicating that the higher the average pairwise correlation, the lower the return of the strategy. Note, though, that the independent variable is constructed by using overlapping data, which could introduce inaccurancy in statistical inference testing (Harri & Brorsen, 2009).[24] Appendix E discusses the problem in detail and argues in favor for the results I obtain. As mentioned above, average pairwise correlation is biased upwards at the beginning of the period due to fewer available contracts. Restricting the sample to observations after January 1985 – when more than 60% of the contracts become available – shows an even stronger relationship. The coefficient becomes significant at the 1% level and decreases to -0.189, while leaving the intercept almost unchanged.

[24]By using return data over 60 days to construct the average pairwise correlation factor, two subsequent values share around 60–70% of the same return data, therefore causing overlapping regressors.

Figure 6.2 and table 6.1 show that while the mean return and risk adjusted performance of the correlation adjusted time series momentum strategy is very similar to that of the standard time series momentum strategy using the SIGN rule, the maximum drawdown is reduced by 2.42% (in absolute terms) and is the best in comparison with the other strategies. The correlation adjusted time series momentum strategy has the lowest volatility among all four strategies and its skewness is almost zero. On the other hand it also has the least dollar growth over the sample period. In the subsample analysis in appendix D I find that correlation adjusted time series momentum does sometimes outperform the standard time series momentum strategy. Especially between June 2009 and June 2015 the strategy is able to reduce the maximum drawdown and volatility compared to the SIGN signal. Still, the correlation adjusted time series momentum strategy has a much higher turnover causing the strategy to be much more expensive.

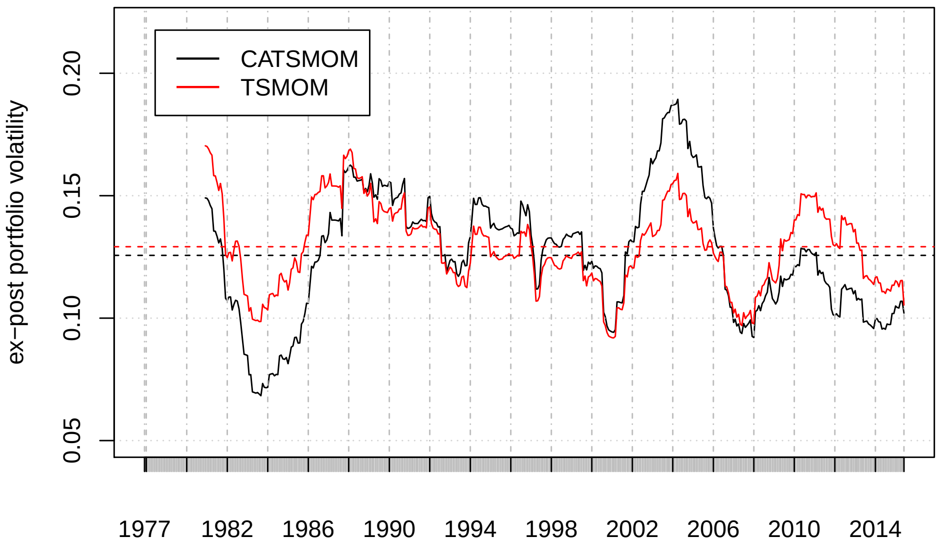

FIGURE 6.4: Ex-post portfolio volatility. The figure plots the ex-post portfolio volatility of the monthly standard SIGN time series momentum strategy (red) and the ex-post portfolio volatility of the monthly correlation adjusted time series momentum strategy (black) over a rolling window of 36 months. The red dashed horizontal line is the mean of the ex-post portfolio volatility of the monthly standard SIGN time series momentum strategy which is equal to 12.92% and the black dashed horizontal line is the mean of the ex-post portfolio volatility of the monthly correlation adjusted time series momentum strategy (CATSMOM) which is equal to 12.56%. The sample period is January 1978 to June 2015.

The correlation adjusted time series momentum strategy targets the overall portfolio volatility level instead of the per asset volatility level and should therefore be better in keeping the portfolio volatility low and steady over time. Figure 6.4 plots the ex-post 36 months running portfolio volatility of the time series momentum strategy using the SIGN signal in red and and the ex-post 36 months running portfolio volatility of the correlation adjusted time series momentum strategy in black. Surprisingly, the standard SIGN time series momentum strategy is better in keeping the ex-post portfolio volatility smooth and it has an annualised standard deviation of only 5.94% while the ex-post annualised portfolio volatility of the correlation adjusted time series momentum strategy exhibits an annualised standard deviation of 8.89%. Still, the mean ex-post volatility of the correlation adjusted time series momentum strategy is at 12.56% and therefore lower and closer to the portfolio volatility level of 12% than the one for the standard SIGN time series momentum strategy at 12.92%.

7. Conclusion

Time series momentum is not without reason one of the trading strategies longest pursued by stock market investors. Hurst et al. (2012) show that a well diversified strategy – build with futures contracts and scaled by the single asset ex-ante volatilities – provides trend followers with annual double digit returns and very low risk for over 100 years now.

According to the efficient market hypothesis from Fama (1970, 1991), time series momentum should not be profitable, since trends in prices should not exist. Still, they might be consistent with a more sophisticated version of market efficiency and various rational theories try to explain why trend followers are able to collect risk premias from other market participants, such as price hedgers. On the other hand, there exists as well a broad literature on behavioural reasons for price trends. Finding out more about the underlying mechanism of time series momentum and whether price trends are due to rational behaviour of market participants or solely due to market inefficiencies and human irrationality is an important task for future research. Only then investors know for sure if the strategy will continue to work in the future or if it might disappear in more efficient markets.

By reproducing and prolonging the time series momentum strategies from Baltas & Kosowski (2013) I find that the daily and weekly time series momentum strategies do not perform well anymore with more recent observations, but the monthly time series momentum strategy continues to deliver impressive excess returns, even when accounting for transaction costs. I find similar return characteristics as Moskowitz et al. (2012). The factor loadings of other risk factors are insignificant except for the cross sectional momentum factor for the weekly and monthly time series momentum strategy. A deeper investigation shows that cross sectional momentum and time series momentum are closely related, but time series momentum is superior since it captures most of cross sectional momentum and produces a significant alpha. Also, cross sectional momentum is prone to crashes and has a lower Sharpe Ratio. Time series momentum returns are able to explain the high returns of CTAs, which performed particularly well during the financial crisis of 2008, when most other funds lost money. Baltas & Kosowski (2013) show that time series momentum is a good hedge against tail events since its returns form a smile when plotted against a market index. I only find the so called "momentum smile" for the daily and weekly strategy, but not for the monthly time series momentum strategy.

To improve the performance of time series momentum, I implement three extensions suggested in the literature. The first is to only consider significantly trending assets when constructing the strategy (Baltas & Kosowski, 2012). I find that this increases the return substantially and lowers turnover, but it comes with the cost of higher volatility and worse drawdowns. The second extension I test is to use a moving average trading rule instead of the SIGN rule. Marshall et al. (2014) show that MAR should give earlier and therefore better signals than SIGN. I cannot confirm their findings over the full period and also a subsample analysis shows that while the return and Sharpe Ratio is almost unaffected by the change in trading signal, the turnover is on average higher for the MAR rule, making the strategy more expensive to apply in practice. Lastly, I implement an average pairwise correlation factor to the weighting scheme of the strategy. Baltas & Kosowski (2014) find that time series momentum does not perform well whenever the correlation between assets increases. In a regression I can confirm this result. The correlation adjusted time series momentum strategy does indeed improve the return statistics in some periods by lowering the volatility and improving the maximum drawdown, but it also increases the turnover substantially, which makes the strategy very expensive. Interestingly, I do not find that correlation adjusted time series momentum does better in keeping the ex-post portfolio volatility stable, even if it targets the portfolio volatility directly.

In my analysis I do not account for the bid/ask spread of futures contracts. This could be considered in a future study on the topic.

A. Yang & Zhang (2000) volatility estimator

The Yang & Zhang (2000) volatility estimator is the first unbiased range based volatility estimator in the literature that accounts for a drift in the price process as well as the opening jump. It is a linear combination of the Rogers & Satchell (1991) estimator, the ordinary standard deviation estimator of daily log-returns and a similar estimator that uses normalised opening prices instead of close to close log-returns. Denote the daily opening, high, low and closing log-prices by $O(t)$, $H(t)$, $L(t)$, $C(t)$ and calculate:

$$\text{normalised opening price: } o(t) = O(t) - C(t-1) \tag{A.1}$$

$$\text{normalised closing price: } c(t) = C(t) - O(t) \tag{A.2}$$

$$\text{normalised high price: } h(t) = H(t) - O(t) \tag{A.3}$$

$$\text{normalised low price: } \ell(t) = L(t) - O(t) \tag{A.4}$$

$$\text{daily close-to-close return: } r(t) = C(t) - C(t-1) \tag{A.5}$$

Let D be the number of days over which the volatility is calculated and 261 the number of trading days per year. The standard deviation estimator (STDEV), opening jump estimator (OPEN) and Rogers & Satchell (1991) estimator (RS) are defined as follows:

$$\sigma^2_{\text{STDEV}}(t, D) = \frac{261}{D} \sum_{i=0}^{D-1} [r(t-i) - \bar{r}(t)]^2 \tag{A.6}$$

$$\sigma^2_{\text{OPEN}}(t, D) = \frac{261}{D} \sum_{i=0}^{D-1} [o(t-i) - \bar{o}(t)]^2 \tag{A.7}$$

$$\sigma^2_{\text{RS}}(t, D) = \frac{261}{D} \sum_{i=0}^{D-1} [h(t-i)(h(t-i) - c(t-i)) + \ell(t-i)(\ell(t-i) - c(t-i))] \tag{A.8}$$

where $\bar{r}(t) = \frac{1}{D}\sum_{i=0}^{D-1} r(t-i)$ and $\bar{o}(t) = \frac{1}{D}\sum_{i=0}^{D-1} o(t-i)$. The Yang & Zhang (2000) volatility estimator can be calculated combining all three estimators:

$$\sigma^2_{\text{YZ}}(t, D) = \sigma^2_{\text{OPEN}}(t, D) + k\sigma^2_{\text{STDEV}}(t, D) + (1-k)\sigma^2_{\text{RS}}(t, D), \tag{A.9}$$

where k is chosen such that the variance of the estimator is minimized, which is achieved in practice for $k = \frac{0.34}{1.34+\frac{D+1}{D-1}}$ (Yang & Zhang, 2000). In accordance with Moskowitz et al. (2012), Baltas & Kosowski (2013) and Hurst et al. (2013) I set $D = 60$ days.

B. Summary statistics of futures contracts

	Exchange	Start	Mean (%)	Vola (%)	Skew	Kurt	SR
AUD/USD	CME	Jan-1987	3.25	11.58	−0.39	4.65	0.28
CAD/USD	CME	Jan-1973	0.15	6.73	−0.36	7.39	0.02
CHF/USD	CME	Jan-1973	0.66	12.43	0.10	3.92	0.05
EUR/USD	CME	Dec-1972	0.15	11.56	0.04	3.71	0.01
GBP/USD	CME	Oct-1975	1.05	10.46	0.03	5.00	0.10
JPY/USD	CME	Jan-1973	−0.38	11.53	0.56	4.84	−0.03
Dollar Index	ICE	Nov-1985	−2.15	8.88	0.35	3.50	−0.24
DJIA	CBOT	Jan-1949	6.04	14.22	−0.45	5.08	0.42
NASDAQ 100	CME	Jan-1985	9.89	24.80	−0.38	4.65	0.40
NYSE Composite	ICE	Jun-1964*	4.81	15.25	−0.49	5.13	0.32
S&P 500	CME	Jan-1949	5.83	14.36	−0.40	4.57	0.41
S&P 400 MidCap	CME	Jan-1981	9.23	16.78	−0.75	5.83	0.55
Russell 2000	ICE	Dec-1978	8.99	19.55	−0.81	5.70	0.46
DJ Stoxx 50	EUREX	Dec-1986	5.43	16.39	−0.87	5.13	0.33
Eurostoxx 50	EUREX	Dec-1986	5.53	18.61	−0.66	4.54	0.30
FTSE 100	NYSE LIFFE	Dec-1983	4.65	15.87	−0.84	6.52	0.29
DAX	EUREX	Sep-1959	4.25	19.42	−0.34	5.01	0.22
CAC 40	Euronext	Jul-1987	4.88	20.17	−0.32	4.27	0.24
IBEX 35	MEFF	Jan-1987	5.46	21.93	−0.49	4.84	0.25
AEX	Euronext	Jan-1983	7.30	20.23	−0.79	5.58	0.36
SMI	EUREX	Jan-1988	8.29	16.17	−0.36	3.81	0.51
MIB 30	BI	Dec-1992	4.75	22.79	0.15	3.45	0.21
S&P Canada 60	MX	Jan-1982	6.16	15.30	−0.70	6.15	0.40
Nikkei 225	CME	May-1949	6.00	20.52	−0.19	4.26	0.29
TOPIX	OSE	Dec-1952	5.50	18.25	−0.18	4.72	0.30
ASX SPI 200	ASX	May-1992	4.72	13.31	−0.63	3.52	0.35
Hang Seng	SEHK	Nov-1969	10.79	32.84	0.23	9.68	0.33
KOSPI 200	KRX	Jan-1990	3.14	30.89	0.80	8.35	0.10
MSCI Taiwan	SGX	Dec-1987	6.17	33.23	0.49	5.35	0.19
MSCI EAFE	NYSE LIFFE	Dec-1981	6.50	17.45	−0.36	3.82	0.37
US 2Y	CBOT	Jun-1990	1.52	1.68	0.19	3.57	0.90
US 5Y	CBOT	May-1988	2.87	4.12	0.06	3.78	0.70
US 10Y	CBOT	May-1982	4.72	6.94	0.20	3.98	0.68
US 30Y	CBOT	Aug-1977	3.24	11.18	0.27	4.76	0.29
Municipal Bonds	CBOT	Jan-1986*	5.00	8.08	−0.56	4.44	0.62
GER 2Y	EUREX	Oct-1998	0.81	1.33	0.14	3.90	0.61
GER 5Y	EUREX	Oct-1998	2.38	3.19	−0.01	2.72	0.74
GER 10Y	EUREX	Oct-1998	3.37	5.23	0.14	2.86	0.64
GER 30Y	EUREX	Sep-2005	5.10	12.52	0.76	4.54	0.41
AUS 3Y	ASX	May-1988	0.65	1.40	−0.15	5.08	0.46

Continued below

	Exchange	Start	Mean (%)	Vola (%)	Skew	Kurt	SR
AUS 10Y	ASX	Dec-1984	0.50	1.31	−0.37	4.69	0.39
UK 10Y	NYSE LIFFE	Nov-1982	2.49	7.53	0.09	4.24	0.33
CAN 10Y	MX	Sep-1989	3.75	6.02	0.00	3.31	0.62
JPN 10Y	OSE	Dec-1986	3.05	5.08	−0.07	8.81	0.60
KOR 3Y	KRX	Sep-1999	2.53	3.15	0.40	5.38	0.80
WTI	NYMEX	Mar-1983	−0.35	24.12	−0.36	6.84	−0.01
Brent	ICE	Sep-2003	3.37	30.84	−0.46	4.31	0.11
Heating Oil	NYMEX	Nov-1978	7.09	30.90	0.87	6.20	0.23
Natural Gas	NYMEX	Apr-1990	−12.61	55.60	0.96	6.02	−0.23
RBOB Gasoline	NYMEX	Dec-1984	6.54	24.66	−0.06	5.53	0.27
Copper	COMEX	Jul-1988	6.98	26.17	0.09	5.85	0.27
Gold	COMEX	Aug-1977	2.55	19.33	0.54	6.61	0.13
Palladium	NYMEX	Nov-1977	5.18	35.57	0.21	6.38	0.15
Platinum	NYMEX	Feb-1973	2.04	27.21	0.52	8.11	0.07
Silver	COMEX	Aug-1973	0.34	35.22	0.82	16.74	0.01
Feeder Cattle	CME	Jul-1978	1.99	14.07	0.10	5.16	0.14
Live Cattle	CME	Jan-1979	1.86	13.95	−0.13	3.97	0.13
Lean Hogs	CME	Jan-1979	−3.17	25.38	0.13	4.20	−0.13
Pork Bellies	CME	Jan-1979*	−6.49	36.19	0.43	4.37	−0.18
Corn	CBOT	Jan-1973	−4.00	26.57	1.02	8.02	−0.15
Oats	CBOT	Apr-1978	−1.35	29.92	2.74	26.93	−0.05
Soybean Oil	CBOT	Dec-1977	−3.73	25.86	0.54	6.10	−0.14
Soybean Meal	CBOT	Jan-1978	6.14	26.13	0.40	4.42	0.23
Soybean	CBOT	Feb-1973	1.45	27.75	0.96	9.10	0.05
Wheat	CBOT	Jan-1978	−5.79	25.62	0.46	5.00	−0.23
Cocoa	ICE	Oct-1977	−6.75	29.00	0.61	4.27	−0.23
Coffee	ICE	Nov-1977	−6.21	37.89	1.12	6.01	−0.16
Cotton	ICE	Oct-1977	−0.43	23.96	0.26	4.92	−0.02
Lumber	CME	Feb-1978	−7.11	24.86	0.22	3.64	−0.29
Orange Juice	ICE	Aug-1977	−2.42	24.56	1.04	7.19	−0.10
Sugar	ICE	Oct-1977	−6.55	37.59	1.26	8.29	−0.17

TABLE B.1: Summary statistics of futures contracts. The table provides summary statistics for all 71 futures contracts using monthly returns calculated from the earliest available date for each contract. The annualised return (mean) and annualised standard deviation (vola) are displayed in percentage terms. Also calculated are the skewness (skew), kurtosis (kurt) and annualised Sharpe Ratio. The start dates indicate from which date on data is available for each contract. All but three contracts have data until 30th June 2015. The time series for the NYSE Composite contract (Sept-2011), Municipal Bond contract (Mar-2006) and Pork Bellies contract (Jul-2011) are indicated by * and end prior due to delisting. The EUR/USD contract is spliced with the DEM/USD contract prior to Mar-1999 and the RBOB Gasoline contract is spliced with the Unleaded Gasoline contract prior to Nov-2005 as in Baltas & Kosowski (2013).

Exchange	Full Name	Location
ASX	Australian Securities Exchange	Sydney
BIX	Borsa Italiana	Milan
CME	Chicago Mercantile Exchange	Chicago
CBOT	Chicago Board of Trade	Chicago
COMEX	Commodity Exchange	New York
EUREX	European Exchange	Frankfurt
Euronext	Euronext	Amsterdam
ICE	Intercontinental Exchange	Atlanta
KRX	Korea Exchange	Seoul
MEFF	Mercado Espanol de Futuros Financieros	Madrid
MX	Montreal Exchange	Montreal
NYMEX	New York Mercantile Exchange	New York
NYSE LIFFE	New York Stock Exchange – London International Financial Futures and Options Exchange	London
OSE	Osaka Stock Exchange	Osaka
SEHK	Hong Kong Stock Exchange	Hong Kong
SGX	Singapore Exchange	Singapore

TABLE B.2: List of futures exchanges. The table lists the full names and locations of the futures exchanges from the dataset.

C. Congruence of time series momentum returns

Since I am building the same time series momentum strategies as Baltas & Kosowski (2013) with a very similar data sample but from different data providers, I want to compare the return series from my strategies with the ones from Baltas & Kosowski (2013).[25]

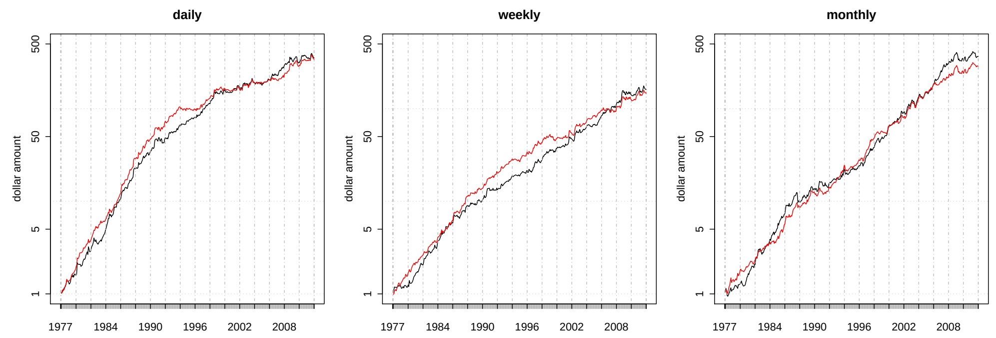

FIGURE C.1: Comparing time series momentum performances. The figures plot the monthly dollar growth of the daily, weekly and monthly time series momentum strategies from Baltas & Kosowski (2013) (in black) versus the dollar growth of my strategies (in red) on a log scale. The sample period is January 1978 to January 2012.

First, one needs to account that the sample is slightly different due to different availabilities of some data. For most contracts I have a different starting date compared with the ones from Baltas & Kosowski (2013), which negatively impacts the fit at the beginning of the time series. Further, Baltas & Kosowski (2013) write that data for the Korea 3Y government bond futures contract is no longer available after June 2011. I have data for it up to June 2015 from Datastream. Instead, my time series for the NYSE Composite index futures contract ends in September 2011, while Baltas & Kosowski (2013) have data up until January 2012. The splicing dates of the equity index futures contracts, the EUR/USD futures contract and the RBOB Gasoline futures contract differ and the end date of the Municipial Bond contract is also slightly different.[26] The

[25]The return series of the daily, weekly and monthly strategies from Baltas & Kosowski (2013) are publicly available on `http://www3.imperial.ac.uk/riskmanagementlaboratory/risklabsections/centreforhedgefundsresearch/baltas_kosowski_factors` (2015-10-15).

[26]For the exact details please compare Baltas & Kosowski (2013), Table I, and table B.1 from appendix B.

discrepancies in data availability surely have an effect on the fit of the return series, even if it should not be too pronounced.

Even so, a first comparison of the return series of my strategies and the ones stemming from Baltas & Kosowski (2013) shows, that they do not fit as well as they should. Figure C.1 plots the log-performances of the daily, weekly and monthly strategies from both me and Baltas & Kosowski (2013) up to January 2012. The black line represents the dollar growth of the time series momentum strategies from Baltas & Kosowski (2013) and the red line the dollar growth of mine (both on a log scale). The correlation of daily and weekly time series momentum returns is 83% and of monthly 79%.

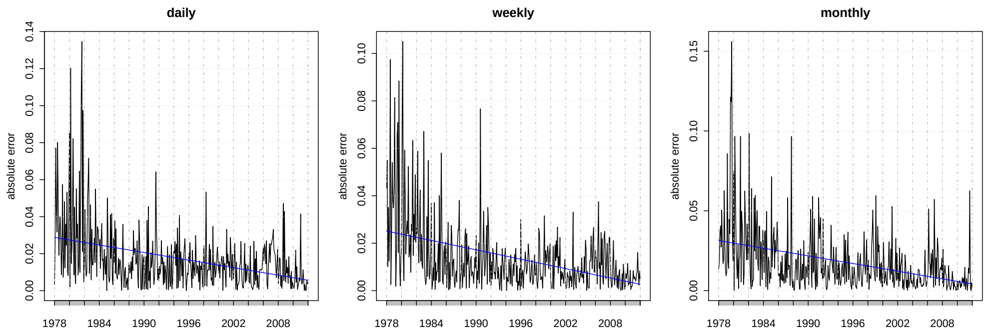

FIGURE C.2: Spread of time series momentum returns. The figures plot the daily, weekly and monthly absolute spread in time series momentum returns between Baltas & Kosowski (2013) and my strategies. The blue line indicates the linear trend. The sample period is January 1978 to January 2012.

Figure C.2 plots the absolute spreads of the return series with a linear trend line in blue. Even if the spread narrows over time for all three strategies, the average difference between my time series momentum returns and the ones from Baltas & Kosowski (2013) over the whole period is still at 1.7% for the daily returns, 1.4% for the weekly returns and 1.8% for the monthly returns. In the last year of data, from February 2011 to January 2012, the spread narrows to a mean of 0.4%, 0.7% and 0.9% respectively.

To test whether the discrepancies are data related I use a subsample of 60 futures contracts from Bloomberg for January 2012 to June 2015 and compare the time series momentum strategy returns from that data sample with the ones I obtain from my original sample from Datastream (using the same subsample).[27] Figure C.3 plots the

[27]The time period and subsample are chosen to maximize data availability and quality. The subsample does exclude data from the Municipial Bond contract, Japan 10Y government bond contract, Korea 3Y government bond contract, NYSE Composite index contract, Eurostoxx 50 index contract, DAX index

absolute spread of the three return series for daily, weekly and monthly time series momentum for the Datastream dataset and the Bloomberg dataset. The blue line represents the mean which is equal to 0.4% for the daily returns, 0.6% for the weekly returns and 0.7% for the monthly returns, comparable with the averages I got for the spreads in the last year of data from Baltas & Kosowski (2013) from above.

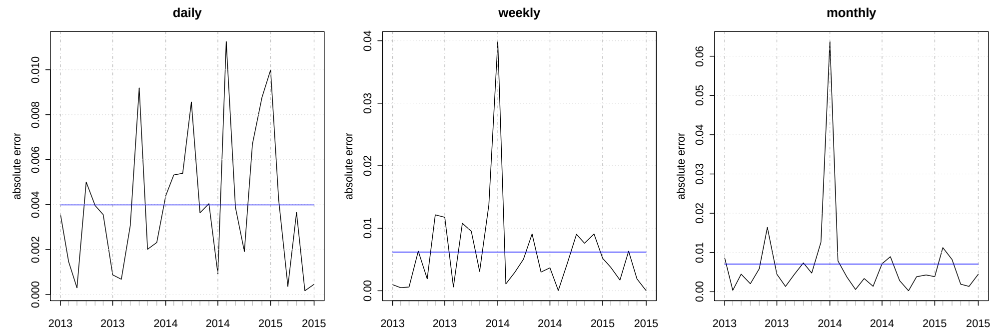

FIGURE C.3: Spreads from using different data providers. The figures plot the daily, weekly and monthly absolute spread in time series momentum returns between data from Datastream and Bloomberg. The blue line indicates the mean. The sample period is January 2013 to June 2015.

It seems that time series momentum returns are very sensitive to differences in the data sample, especially due to the volatility weighting factor. The factor is calculated by using daily opening, high, low and closing prices and data quality does differ especially for the first three variables among data providers. Still, time series momentum yields high positive mean returns for all tested data samples, indicating that the performance of time series momentum is robust for different data samples.

contract, MIB 30 index contract, TOPIX index contract, ASX SPI 200 index contract, KOSPI 200 index contract and Pork Bellies contract.

D. Subsample analysis for time series momentum extensions

A subsample analysis of the different time series momentum strategies is helpful in assessing, whether the extensions are really useful to improve time series momentum performance. In table D.1 I split the period between January 1978 to June 2015 in five subperiods. The first three subsamples are approximately ten year periods: from January 1978 to December 1987 (period 1), from January 1988 to December 1997 (period 2) and from January 1998 to May 2009 (period 3). The last two periods are the ones also considered in chapter 5.1, from June 2009 to January 2012 (period 4) and from February 2012 to June 2015 (period 5). Both cover approximately two and a half years of data. The first period is interesting since monthly time series momentum seems not to perform that well anymore in those years after the financial crisis of 2008 and the second period are the additional years of data I add to the analysis of Baltas & Kosowski (2013).

	SIGN	TREND	MAR	CATSMOM
Period 1	Jan–1978 to Dec–1987			
Mean (%)	24.39	25.12	26.94	19.60
Volatility (%)	14.83	19.01	15.63	13.11
Skewness	−0.53	−0.68	−0.70	−0.62
Kurtosis	3.50	4.26	5.16	4.41
Sharpe Ratio	1.64	1.32	1.72	1.50
MDD (%)	11.66	22.61	16.24	12.99
Dollar growth	8.87	9.40	10.87	5.99
turnover (%)	366.37	364.91	407.67	1059.44
avg. holdings	266.30	188.49	268.55	127.53
Period 2	Jan–1988 to Dec–1997			
Mean (%)	18.21	17.83	16.96	19.11
Volatility (%)	12.87	16.35	12.45	13.55
Skewness	0.16	0.06	0.03	0.13
Kurtosis	3.19	3.29	3.24	3.41
Sharpe Ratio	1.42	1.09	1.36	1.41
MDD (%)	14.88	24.86	11.02	14.37
Dollar growth	5.33	5.16	4.79	5.75
turnover (%)	324.55	335.87	388.74	406.40
avg. holdings	649.60	467.70	651.22	790.08
Period 3	Jan–1998 to May–2009			
Mean (%)	15.60	19.06	15.12	17.44
Volatility (%)	12.46	14.81	12.96	13.27
Skewness	−0.08	−0.12	0.24	0.20
Kurtosis	3.20	3.21	4.01	3.46

Continued below

	SIGN	TREND	MAR	CATSMOM
Sharpe Ratio	1.25	1.29	1.17	1.32
MDD (%)	15.40	16.01	14.78	15.81
Dollar growth	5.23	7.33	4.99	6.27
turnover (%)	322.78	317.52	405.81	752.81
avg. holdings	792.51	562.39	793.52	619.35
Period 4	Jun–2009 to Jan–2012			
Mean (%)	5.84	8.73	8.51	4.64
Volatility (%)	12.10	14.34	12.46	9.63
Skewness	−0.46	−0.26	−0.38	−0.45
Kurtosis	3.13	2.11	2.13	3.24
Sharpe Ratio	0.48	0.61	0.68	0.48
MDD (%)	9.99	19.65	9.23	8.15
Dollar growth	1.16	1.25	1.24	1.13
turnover (%)	315.53	375.59	378.20	291.97
avg. holdings	798.12	544.09	798.12	1391.92
Period 5	Feb–2012 to Jun–2015			
Mean (%)	15.25	19.59	9.72	16.36
Volatility (%)	11.93	14.22	10.23	10.96
Skewness	0.09	0.08	−0.54	−0.05
Kurtosis	4.58	3.37	2.87	3.51
Sharpe Ratio	1.28	1.38	0.95	1.49
MDD (%)	8.09	6.55	6.90	6.71
Dollar growth	1.62	1.84	1.37	1.68
turnover (%)	384.10	270.41	401.32	481.14
avg. holdings	1196.33	912.52	1196.33	2041.18

TABLE D.1: Subsample analysis for time series momentum extensions. This table shows a summary of the performance of the monthly time series momentum strategy when using the SIGN signal, TREND signal, MAR signal and correlation adjusted time series momentum (CATSMOM) from January 1978 to December 1987 (period 1), from January 1988 to December 1997 (period 2), from January 1998 to May 2009 (period 3), from June 2009 to January 2012 (period 4) and from February 2012 to June 2015 (period 5). The annualised return (mean), annualised standard deviation (volatility) and maximum drawdown are displayed in percentage terms. The Sharpe Ratio is in annualised terms. $ growth indicates the amount an investment of 1$ would have grown to over the relevant period. The turnover is annualised and in percentage terms (see chapter 6.1 for the definition) and the average holdings is the number of monthly average holdings summed over all assets in absolute terms (long and short).

Baltas & Kosowski (2012) claim that by using the TREND rule instead of the SIGN rule, time series momentum returns should increase, since only assets that are significantly trending are traded. The idea is that in times of less available trends, time series momentum does not perform well and therefore the exposure to the strategy is reduced by investing in less assets. Also, the turnover can be substantially lowered by only investing in significantly trending assets. In chapter 6.2 I show that this holds true for the whole period, but comes with the cost of higher volatility due to less diversification benefits – causing the Sharpe Ratio to decrease. The subsample analysis from table D.1 confirms my findings for the full period. The return of the TREND signal is higher in almost all subperiods compared to the SIGN signal and turnover as well as the average holdings are lower. Surprisingly, I find that also the Sharpe Ratio is higher in three of the five subsamples, especially in the last two periods. The maximum drawdown on the other hand is almost always substantially worse for the TREND signal.

Marshall et al. (2014) claim that using the MAR rule instead of the SIGN rule should also improve time series momentum performance, since it gives earlier signals. In chapter 3.2.1 I show that the MAR rule changes sign, whenever the price of an asset moves above or below the MA. The SIGN rule on the other hand changes sign, whenever the MA changes direction, which happens less often. Over the whole period this seems not to work according to the results from chapter 6.3. The subsample analysis confirms also in this case what I find in the full sample. The MAR rule adds no additional value to time series momentum. It performs very similar compared to the SIGN rule and is in some periods slightly better and in some periods slightly worse. Still, turnover is always higher given almost the same average holdings, causing the strategy to be more expensive than time series momentum constructed with the SIGN rule.

Time series momentum does not perform well whenever the average pairwise correlation between assets increases. In chapter 6.4 I argue that the correlation adjusted time series momentum strategy (which reduces the exposure to the strategy whenever the average pairwise correlation factor from equation 3.19 increases) successfully lowers the maximum drawdown but leaves the Sharpe Ratio unchanged. On the other hand, correlation adjusted time series momentum increases turnover and is therefore more costly than time series momentum using the SIGN rule. The subsample analysis shows that correlation adjusted time series momentum does in some periods add additional value to time series momentum. Due to its much higher turnover and average holdings over all subperiods it is a very expensive strategy, but is able to reduce the maximum drawdown and volatility in almost all periods and most substantially in the last two subsamples.

E. OLS with overlapping data

The average pairwise correlation factor is built by using overlapping data and thus its usage as regressor in a standard OLS model can cause biased results in statistical inference testing (Harri & Brorsen, 2009). The factor is constructed with daily returns over a lookback period of 60 days (see equation 3.19), which implies that when using month-end values as regressors in table 6.2, around 60–70% of the return time series used to construct the correlation factor is overlapping for two subsequent values.

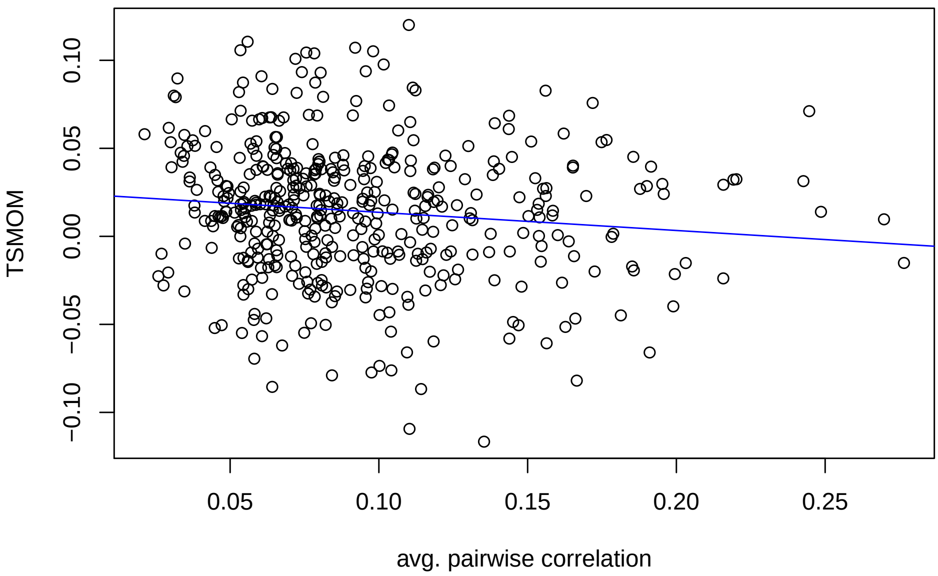

FIGURE E.1: Time series momentum versus average pairwise correlation. The figure plots monthly time series momentum retuns against the average pairwise correlation factor, which is measured over a 60 day period and calculated at each month-end. The blue line indicates the linear trend. The sample period is January 1978 to June 2015.

Most literature discussing the overlapping data problem covers different and mainly simpler forms of overlapping regressors, such as for instance yearly returns that are calculated from January to December, February to January and so on and is therefore not much of a help in my case. Harri & Brorsen (2009) show for example that OLS in combination with Newey & West (1987) t-statistics provides asymptotically valid hypothesis tests when dealing with overlapping observations in the aforementioned simpler form.

The OLS coefficient estimates are unbiased and consistent but inefficient. They find that OLS and Newey & West (1987) t-statistics provide a good fit to the true parameters only if the number of observations is sufficiently large (more than 500) and the number of overlapping observations is not too high (close to 1). Still, the standard deviation is generally underestimated and therefore true null hypotheses are rejected too often by Newey & West (1987).

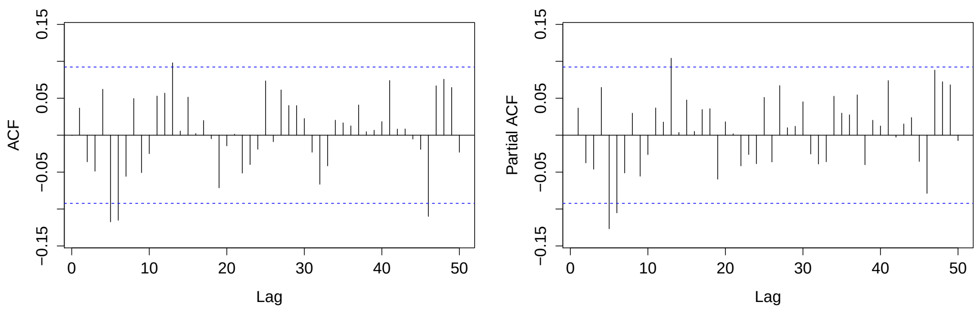

FIGURE E.2: Autocorrelation and partial autocorrelation function of regression residuals. The plot shows the autocorrelation function of the residuals from the regression in table 6.2 on the left and its partial autocorrelation function on the right. The confidence interval is 95% and is given by the dashed blue line. The sample period is January 1978 to June 2015.

Figure E.1 plots the relationship between monthly time series momentum returns and the average pairwise correlation factor. The blue line is the linear fit according to table 6.2. The negative relationship is evident from the plot and not driven by outliers, even if the observations are quite dispersed. Further, the plot shows a relatively symmetric distribution of the observations around the fitted line.

To check whether the results from table 6.2 are biased, it is necessary to conduct some residual diagnostics from the regression. Gilbert (1986) shows that overlapping observations create a MA error term, that causes biased statistical inference testing. Figure E.2 plots the autocorrelation and partial autocorrelation function of the residuals from the regression. There is no obvious structure visible from the plots, even if some lags do exceed the boundary. Further, an unreported regression of the residuals on their first lags does not indicate any autocorrelation. To adress the hypothesis that the residuals follow a MA process, I estimate MA(q) models with varying order q for the residuals using a maximum likelihood procedure, but do not find a good fit.[28]

[28]This analysis is also unreported.

	TSMOM
Intercept	0.022842^{***}
	(6.482758)
avg. pairwise correlation (20 days)	-0.094550^{**}
	(-2.655855)
R^2 (%)	1.58
adj. R^2 (%)	1.36
Num. obs.	450

$^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$

TABLE E.1: Average pairwise correlation and time series momentum returns for 20 days lookback period. Monthly time series momentum returns using the SIGN signal are regressed on the average pairwise correlation factor calculated as in equation 3.19, but $\rho_{i,j}$ is measured over a period of 20 days instead of 60 days for all assets where data exists at each point in time, to avoid the problem of overlapping data. Newey & West (1987) t-statistics are reported in brackets underneath the regression coefficients. The sample period is January 1978 to June 2015.

Another robustness check for the result is to eliminate the overlapping data problem by reducing the time period over which the average pairwise correlation parameter is calculated from 60 days to 20 days. The coefficient in table E.1 is of almost the same size but even more significant, thus supporting the conclusion I draw in chapter 6.4 and indicating even more that inference in the original model is correct.

F. Code

In the following section I present the code I use to construct the time series momentum strategies. The code is written in R.

F.1 Data preparation

To construct the time series momentum strategies I obtain daily open, high, low and closing prices as well as daily volume of 71 futures contracts from Datastream. The data is imported into R from a csv-file. The equity index spot prices I use to backfill equity index futures prices come from Global Financial Data are imported in the same way. It is necessary to bring the data into a useful format as well as to reorganize the column headers in a way such that the futures contracts can be organized chronologically. To handle time-based data in a simple and efficient ways I use the xts package.

```
require(xts)

currencies<-c("AUDUSD","CADUSD","CHFUSD","EURUSD","GBPUSD","JPYUSD","
    Dollar_Index")
interest_rates<-c("US2Y","US5Y","US10Y","US30Y","Muni","GER2Y","GER5Y
    ","GER10Y","GER30Y","AUS3Y","AUS10Y","UK10Y","CAN10Y","JPN10Y","
    KOR3Y")
equities<-c("DJIA","NASDAQ100","NYSE_Composite","S&P500","S&P400_
    MidCap","Russell2000","DJ_Stoxx50","Eurostoxx50","FTSE100","DAX","
    CAC40","IBEX35","AEX","SMI","MIB30","S&P_Canada60","Nikkei225","
    TOPIX","ASX_SPI200","Hang_Seng","KOSPI200","MSCI_Taiwan","MSCI_
    EAFE")
commodities<-c("WTI","Brent","Heating_Oil","Natural_Gas","RBOB_
    Gasoline","Unleaded_Gasoline","Copper","Gold","Palladium","
    Platinum","Silver","Feeder_Cattle","Live_Cattle","Lean_Hogs","Pork
    _Bellies","Corn","Oats","Soybean_Oil","Soybean_Meal","Soybeans","
    Wheat","Cocoa","Coffee","Cotton","Lumber","Orange_Juice","Sugar")
securities<-c(currencies,interest_rates,equities,commodities)

security<-securities[i]

#import price data for each security
data<-read.csv(paste(security,".csv",sep=""),header=TRUE,sep=";")
```

The column headers are reorganized such that the first six positions list the delivery year and month of the contract. Due to the fact that the headers are very heterogenous this step must be done by hand for each contract i. The position of the year and month varies for each futures contract, so the code from below is just an example and does not fit for all contracts.

```
des<-colnames(data)[-1] #extract header to reorder
des<-gsub("..",".",des,fixed=TRUE) #remove multiple dots
des<-strsplit(des,"\\.") #split headers
year<-sapply(des,function(x) x[6]) #save year
mon<-sapply(des,function(x) x[5]) #save month
mon<-months(mon) #transform month to number
des<-paste(paste(year,mon,sep=""),sapply(des,function(x) x[7]),sapply
    (des,function(x) x[8]),sep=".")
colnames(data)<-c("date",des) #add updated headers
```

The function “months” is defined as following:

```
months <- function(mon){
  mo.name<-c("JAN","FEB","MAR","APR","MAY","JUN","JUL","AUG","SEP","
      OCT","NOV","DEC")
  mo.num<-c("01","02","03","04","05","06","07","08","09","10","11","
      12")
   pos<-match(mon,mo.name)
  mon<-mo.num[pos]
   return(mon)
}
```

Now that the column headers are in a more useful format the futures contracts can be reorganized chronologically and saved in the xts-format. For contracts that are spliced together (such as the EUR/USD contract with the DEM/USD contract and the RBOB Gasoline contract with the Unleaded Gasoline contract) I merge both price data tables.

```
data<-data[,order(substr(names(data),1,6))] #order chronologically
times<-as.Date(data[-nrow(data),ncol(data)],"%d.%m.%Y") #save times
    from data table
data<-apply(apply(data[,-ncol(data)], 2, gsub, patt=",", replace=".")
    , 2, as.numeric) #replace comma by dot and make numeric
data<-as.xts(data,order.by=times) #save as xts
```

In the next step I split up “data” into separate tables for the open, high, low and closing prices as well as the volume of each contract.

```
pr<-assign(paste(security,"close",sep="."),data[,seq(1, ncol(data),
    5)]) #save as pr and separatly for each security
assign(paste(security,"open",sep="."),data[,seq(2, ncol(data), 5)])
assign(paste(security,"high",sep="."),data[,seq(3, ncol(data), 5)])
assign(paste(security,"low",sep="."),data[,seq(4, ncol(data), 5)])
```

```
vol<-assign(paste(security,"volume",sep="."),data[,seq(5, ncol(data),
    5)])
```

F.2 Calculation of the return series

The variables "pr" and "vol" are used to construct the daily, weekly and monthly return series for each futures contract by always holding the contract with the highest traded volume[29] and by reinvesting the full amount. "w" is the ratio between the price of the old contract (currently held) and the price of the new contract (which will be bought). If the old contract is sold at a higher price than the one from the new contract, more than one new contract is bought and vice versa. It is assumed that contracts are arbitrarily divisible.

```
#overwrite NAs in daily volume table
vol[is.na(vol)] <- 0

#find most traded contract for each time i:
invest<-as.xts(matrix(NA,nrow=nrow(pr),ncol=1), order.by=index(pr))
j<-1
for (i in 1:(nrow(pr)-1)){
  if (as.numeric(vol[i,j])>=as.numeric(vol[i,j+1]) && !is.na(pr[i+1,j
      ]) ){
    invest[i,1]<-substr(colnames(vol[i,j]),1,6)
  }else{
    invest[i,1]<-substr(colnames(vol[i,j+1]),1,6)
    j<-j+1}
}
invest[nrow(invest)]<-invest[nrow(invest)-1] #fill last row forward
assign(paste(security,"invest",sep="."),invest)

#Splice price vector together
w<-1
pf<-as.xts(matrix(NA,nrow=nrow(pr),ncol=1), order.by=index(pr))
pf[1]<-w*pr[1,which(substr(colnames(pr),1,6)==as.character(invest[1])
    )]
for (i in 2:nrow(pr)){
  if (as.character(invest[i])==as.character(invest[i-1])){
    pf[i]<-w*pr[i,which(substr(colnames(pr),1,6)==as.character(invest
        [i]))]
  }else{
    w<-as.numeric(w*pr[i,which(substr(colnames(pr),1,6)==as.character
        (invest[i-1]))]/pr[i,which(substr(colnames(pr),1,6)==as.
        character(invest[i]))])
```

[29] After rolling forward in the next contract it is not possible to jump back in the old one. If the traded volume of the next contract does not exceed the volume of the currently held contract until its expiration, the contract is rolled forward at the last trading day.

```
    pf[i]<-w*pr[i,which(substr(colnames(pr),1,6)==as.character(invest
        [i]))]
  }
}
colnames(pf)<-paste(security,sep="")
ret<-diff(pf)/lag(pf,1) #calculate daily returns
assign(paste("ret.d",security,sep="."),ret)
ret[1]<-0
assign(paste("perf",security,sep="."),cumprod(1+ret)) #calculate
    performance
assign(paste("ret.m",security,sep="."),diff(apply.monthly(get(paste("
    perf",security,sep=".")), last))/lag(apply.monthly(get(paste("perf
    ",security,sep=".")), last),1)) #calculate monthly returns
assign(paste("ret.w",security,sep="."),diff(get(paste("perf",security
    ,sep="."))[.indexwday(get(paste("perf",security,sep="."))) %in%
    3])/lag(get(paste("perf",security,sep="."))[.indexwday(get(paste("
    perf",security,sep="."))) %in% 3],1)) #calculate weekly returns
```

F.3 Calculation of the Yang & Zhang (2000) volatility estimator

From the daily open, high, low and closing prices I calculate the Yang & Zhang (2000) volatility estimator. The daily log-prices are normalized according to the definition and then spliced together to a single vector, so that for each point in time I extract the relevant value according to the then held contract. The estimator is calculated over a period of 60 days. For missing values I interpolate linearly.

```
#normalize daily log-prices
assign(paste(security,"norm.open",sep="."),log(get(paste(security,"
    open",sep=".")))-log(lag(get(paste(security,"close",sep=".")),1)))
assign(paste(security,"norm.close",sep="."),log(get(paste(security,"
    close",sep=".")))-log(get(paste(security,"open",sep="."))))
assign(paste(security,"norm.high",sep="."),log(get(paste(security,"
    high",sep=".")))-log(get(paste(security,"open",sep="."))))
assign(paste(security,"norm.low",sep="."),log(get(paste(security,"low
    ",sep=".")))-log(get(paste(security,"open",sep="."))))
assign(paste(security,"norm.c.c",sep="."),log(get(paste(security,"
    close",sep=".")))-log(lag(get(paste(security,"close",sep=".")),1))
    )

norm.open<-norm.close<-norm.high<-norm.low<-norm.c.c<-as.xts(matrix(
    NA,nrow=nrow(pr),ncol=1), order.by=index(pr))

#splice normalized daily log-prices together
for (i in 2:nrow(pr)){
  norm.open[i]<-get(paste(security,"norm.open",sep="."))[i,which(
      substr(colnames(pr),1,6)==as.character(invest[i]))]
  norm.close[i]<-get(paste(security,"norm.close",sep="."))[i,which(
      substr(colnames(pr),1,6)==as.character(invest[i]))]
```

```
  norm.high[i]<-get(paste(security,"norm.high",sep="."))[i,which(
      substr(colnames(pr),1,6)==as.character(invest[i]))]
  norm.low[i]<-get(paste(security,"norm.low",sep="."))[i,which(substr
      (colnames(pr),1,6)==as.character(invest[i]))]
  norm.c.c[i]<-get(paste(security,"norm.c.c",sep="."))[i,which(substr
      (colnames(pr),1,6)==as.character(invest[i]))]
}
norm.open<-assign(paste(security,"norm.open",sep="."),na.approx(norm.
    open, method = "linear", na.rm = FALSE, maxgap=2))
norm.close<-assign(paste(security,"norm.close",sep="."),na.approx(
    norm.close, method = "linear", na.rm = FALSE, maxgap=2))
norm.high<-assign(paste(security,"norm.high",sep="."),na.approx(norm.
    high, method = "linear", na.rm = FALSE, maxgap=2))
norm.low<-assign(paste(security,"norm.low",sep="."),na.approx(norm.
    low, method = "linear", na.rm = FALSE, maxgap=2))
norm.c.c<-assign(paste(security,"norm.c.c",sep="."),na.approx(norm.c.
    c, method = "linear", na.rm = FALSE, maxgap=2))

#calculate YZ volatility estimator
D<-60
k<-0.34/(1.34+(D+1)/(D-1))

var.stdev<-var.open<-var.rs<-as.xts(matrix(NA,nrow=nrow(pr),ncol=1),
    order.by=index(pr))

for (i in (D+1):nrow(get(paste(security,"norm.open",sep=".")))) {
  var.stdev[i]<-261/D*sum((norm.c.c[i:(i-(D-1))]-mean(norm.c.c[i:(i-(
      D-1))]))^2)
  var.open[i]<-261/D*sum((norm.open[i:(i-(D-1))]-mean(norm.open[i:(i
      -(D-1))]))^2)
  var.rs[i]<-261/D*sum(norm.high[i:(i-(D-1))]*(norm.high[i:(i-(D-1))
      ]-norm.close[i:(i-(D-1))])+norm.low[i:(i-(D-1))]*(norm.low[i:(i
      -(D-1))]-norm.close[i:(i-(D-1))]))
}
var.yz<-var.open+k*var.stdev+(1-k)*var.rs

assign(paste(security,"var.yz",sep="."),var.yz)
```

The code is run for each of the 71 futures contracts to get a daily, weekly and monthly return and performance series and the corresponding Yang & Zhang (2000) volatility estimator.

F.4 Calculation of time series momentum returns

To calculate time series momentum returns the return, volatility and performance data is merged together. Some adjustments are necessary before splitting the data for the daily, weekly and monthly strategies. The start date is fixed as 1st January 1978 and the end date as 30th June 2015.

```
start<-as.Date("1978-01-01") #start date
end<-as.Date("2015-06-30") #end date
period<-paste(start-1,"/",end,sep="")

#aggregates for return data, volatility data and performance data
agg.ret.d<-agg.vol<-agg.vol.stdev<-agg.vol.mop<-agg.perf<-xts(order.
    by=time.d)
agg.ret.w<-xts(order.by=time.w)
agg.ret.m<-xts(order.by=time.m)
for (i in 1:length(securities)) {
  agg.ret.d<-merge(agg.ret.d,get(paste("ret.d",securities[i],sep=".")
      ))
  agg.ret.w<-merge(agg.ret.w,get(paste("ret.w",securities[i],sep=".")
      ))
  agg.ret.m<-merge(agg.ret.m,get(paste("ret.m",securities[i],sep=".")
      ))
  agg.vol<-merge(agg.vol,get(paste(securities[i],"var.yz",sep=".")))
  agg.perf<-merge(agg.perf,get(paste("perf",securities[i],sep=".")))
}
colnames(agg.vol)<-securities

#bring monthly data to standard format (omit multiple days per month)
agg.ret.m<-na.approx(agg.ret.m, method = "constant", na.rm = FALSE,
    maxgap=3)
agg.ret.m<-apply.monthly(agg.ret.m,mean)

for (i in 1:ncol(agg.ret.d)){ #replace NAs which were introduced
    from merging (only for inbetween NAs)
  ret.na<-which(is.na(agg.ret.d[min(which(!is.na(agg.ret.d[,i]))):max
      (which(!is.na(agg.ret.d[,i]))),i]))+min(which(!is.na(agg.ret.d[,
      i])))-1
  agg.ret.d[ret.na,i]<-0
  ret.na<-which(is.na(agg.ret.w[min(which(!is.na(agg.ret.w[,i]))):max
      (which(!is.na(agg.ret.w[,i]))),i]))+min(which(!is.na(agg.ret.w[,
      i])))-1
  agg.ret.w[ret.na,i]<-0
  ret.na<-which(is.na(agg.ret.m[min(which(!is.na(agg.ret.m[,i]))):max
      (which(!is.na(agg.ret.m[,i]))),i]))+min(which(!is.na(agg.ret.m[,
      i])))-1
  agg.ret.m[ret.na,i]<-0
}

#save performance separately
agg.perf<-na.approx(agg.perf, method = "constant", na.rm = FALSE,
    maxgap=3) #fill performance forward
agg.perf.d<-agg.perf
agg.perf.w<-agg.perf[index(agg.ret.w)] #extract weekly performance
agg.perf.m<-agg.perf[index(agg.ret.m)] #extract monthly performance

#save volatility estimator separately
agg.vol.d<-na.approx(agg.vol, method = "constant", na.rm = FALSE,
    maxgap=3) #fill NAs forward which were introduced from merging (
    only for inbetween NAs)
agg.vol.d<-agg.vol.d[period]
agg.vol.w<-agg.vol.d[index(agg.ret.w)]
```

```
agg.vol.m<-agg.vol.d[index(agg.ret.m)]

#save returns from t to t+1 (for strategy)
lag.agg.ret.d<-lag(agg.ret.d,-1) #return for t to t+1
lag.agg.ret.w<-lag(agg.ret.w,-1)
lag.agg.ret.m<-lag(agg.ret.m,-1)
lag.agg.ret.d<-lag.agg.ret.d[period]
lag.agg.ret.w<-lag.agg.ret.w[period]
lag.agg.ret.m<-lag.agg.ret.m[period]

agg.ret.d<-agg.ret.d[period]
agg.ret.w<-agg.ret.w[period]
agg.ret.m<-agg.ret.m[period]
```

F.4.1 Time series momentum signals

The standard time series momentum strategy is constructed by looking whether the return of the strategy was positive or negative over the lookback period. This can be easily checked by comparing the two corresponding entries in the performance time series.

```
###SIGN construction for daily, weekly and monthly strategy
sign.d<-sign(agg.perf.d-lag(agg.perf.d,15))
sign.d<-sign.d[period]
sign.d<-signzero(sign.d) #use function signzero to invest if
    performance is zero
sign.w<-sign(agg.perf.w-lag(agg.perf.w,8))
sign.w<-sign.w[period]
sign.w<-signzero(sign.w)
sign.m<-sign(agg.perf.m-lag(agg.perf.m,12))
sign.m<-sign.m[period]
sign.m<-signzero(sign.m)

#save number of held contracts
ex.ret.d<-abs(sign(sign.d)) #1 if data exists and futures contract is
     traded, 0 else
ex.ret.w<-abs(sign(sign.w))
ex.ret.m<-abs(sign(sign.m))
ex.ret.d<-ex.ret.d[period]
ex.ret.w<-ex.ret.w[period]
ex.ret.m<-ex.ret.m[period]
```

The function "signzero" is defined in the following way:

```
signzero <- function(x){
  zeros<-which(x==0,arr.ind=T)
  if (length(zeros)!=0){
  for (i in 1:nrow(zeros)){
    r<-zeros[i,1]
```

```
    c<-zeros[i,2]
    x[r,c]<-1
  }}
  return(x)
}
```

For the construction of the TREND signal I use the packages "sandwich" and "lmtest" to calculate Newey & West (1987) t-statistics.

```
require("sandwich")
require("lmtest")

#TREND
sig.sign.m<-as.xts(matrix(NA,nrow=nrow(agg.perf.m),ncol=ncol(agg.perf
    .m)), order.by=index(agg.perf.m))
trend<-seq(1,12,1)
for (i in 1:ncol(agg.perf.m)){
  k<-min(which(!is.na(agg.perf.m[,i])))-1
  for (j in (min(which(!is.na(agg.perf.m[,i])))+11):max(which(!is.na(
      agg.perf.m[,i])))){
    span<-as.vector(agg.perf.m[(1+k):j,i])
    test<-lm(span~trend)
    signif<-coeftest(test,vcov=NeweyWest(test,lag=NULL,adjust=TRUE,
        prewhite=FALSE))[2,"t value"]
    if(is.finite(signif) & abs(signif)>=2){
      sig.sign.m[j,i]<-sign(signif)
    }else{
      sig.sign.m[j,i]<-0
    }
    k<-k+1
  }
}
sig.sign.m<-sig.sign.m[period]

#save number of held contracts
sig.ex.ret.m<-abs(sign(sig.sign.m))
sig.ex.ret.m<-sig.ex.ret.m[period]

#MAR
ma.sign.m<-as.xts(matrix(NA,nrow=nrow(agg.perf.m),ncol=ncol(agg.perf.
    m)), order.by=index(agg.perf.m))
for (i in 1:ncol(agg.perf.m)){
  k<-min(which(!is.na(agg.perf.m[,i])))-1
  for (j in (min(which(!is.na(agg.perf.m[,i])))+11):max(which(!is.na(
      agg.perf.m[,i])))){
    avg<-mean(agg.perf.m[(1+k):j,i])
    if((agg.perf.m[j,i]-avg)!=0){
      ma.sign.m[j,i]<-sign(agg.perf.m[j,i]-avg)
    }else{
      ma.sign.m[j,i]<-0
    }
    k<-k+1
  }
}
```

```
ma.sign.m<-ma.sign.m[period]

#save number of held contracts
ma.ex.ret.m<-abs(sign(ma.sign.m))
ma.ex.ret.m<-ma.ex.ret.m[period]
```

To construct the CATSMOM strategy I additionally calculate the average pairwise correlation factor from daily returns of all 71 contracts over a lookback period of 60 days.

```
avg_cov.d<-as.xts(matrix(NA,nrow=nrow(agg.ret.d),ncol=1),order.by=
    index(agg.ret.d))
for (i in 60:nrow(agg.ret.d)){
  corr<-agg.ret.d[(i-59):i,]
  #corr[is.na(corr)]<-0
  corr<-cor(corr, use="pairwise.complete.obs")
  n<-ncol(corr[,colSums(is.na(corr))!=nrow(corr)])
  corr<-sum(corr[upper.tri(corr, diag = FALSE)],na.rm=TRUE)
  avg_cov.d[i]<-2*corr/(n*(n-1))
}
avg_cov.d<-avg_cov.d[period]
avg_cov.m<-avg_cov.d[index(agg.ret.m)]
```

F.4.2 Time series momentum returns

By using the different signals as well as the average pairwise correlation factor for CATSMOM it is now possible to calculate the time series momentum returns. The single asset target volatility is set to 40% and the target portfolio volatility to 12%.

```
vol.target<-0.4
pf.vol.target<-0.12

#SIGN
TSMOM.d<-lag(as.xts(1/rowSums(ex.ret.d,na.rm=T)*rowSums(sign.d*lag.
    agg.ret.d*vol.target/sqrt(agg.vol.d),na.rm=T),order.by=index(agg.
    ret.d)),1) #returns from t-1 to t
TSMOM.w<-lag(as.xts(1/rowSums(ex.ret.w,na.rm=T)*rowSums(sign.w*lag.
    agg.ret.w*vol.target/sqrt(agg.vol.w),na.rm=T),order.by=index(agg.
    ret.w)),1)
TSMOM.m<-lag(as.xts(1/rowSums(ex.ret.m,na.rm=T)*rowSums(sign.m*lag.
    agg.ret.m*vol.target/sqrt(agg.vol.m),na.rm=T),order.by=index(agg.
    ret.m)),1)

#TREND
sig.TSMOM.m<-lag(as.xts(1/rowSums(sig.ex.ret.m,na.rm=T)*rowSums(sig.
    sign.m*lag.agg.ret.m*vol.target/sqrt(agg.vol.m),na.rm=T),order.by=
    index(agg.ret.m)),1)

#MAR
```

```
ma.TSMOM.m<-lag(as.xts(1/rowSums(ma.ex.ret.m,na.rm=T)*rowSums(ma.sign
    .m*lag.agg.ret.m*vol.target/sqrt(agg.vol.m),na.rm=T),order.by=
    index(agg.ret.m)),1)

#CATSMOM
CATSMOM.m<-lag(xts(1/rowSums(ex.ret.m,na.rm=T)*sqrt(rowSums(ex.ret.m,
    na.rm=T)/(1+(rowSums(ex.ret.m,na.rm=T)-1)*avg_cov.m))*rowSums(sign
    .m*lag.agg.ret.m*pf.vol.target/sqrt(agg.vol.m),na.rm=T),order.by=
    index(agg.ret.m)),1)
```

F.4.3 Cross sectional momentum returns

In chapter 5.2.1 I compare monthly time series momentum returns with monthly cross sectional momentum returns. The CSMOM strategy is calculated by using the package Matrix.

```
require(Matrix)

sign.CSMOM.m<-as.xts(matrix(NA,nrow=nrow(agg.perf.m),ncol=ncol(agg.
    perf.m)), order.by=index(agg.perf.m))
colnames(sign.CSMOM.m)<-colnames(agg.perf.m)
ranks<-(agg.perf.m-lag(agg.perf.m,12))/lag(agg.perf.m,12)
ranks<-as.xts(t(apply(ranks,1,rank, ties.method="random",na.last="
    keep"))) #71 is best performance
numbers<-as.xts(apply(ranks,1,nnzero,na.counted = FALSE))
for (i in 1:nrow(numbers)){
  if (numbers[i]>10){
    cut<-numbers[i]/5
    for (j in 1:ncol(ranks)){
      if (!is.na(ranks[i,j])){
      if (ranks[i,j]<=cut){
        sign.CSMOM.m[i,j]<-sign(-1)
      }else{
        if (ranks[i,j]>=(4*cut)){
          sign.CSMOM.m[i,j]<-sign(1)
        }
      }
    }
  }}
}
sign.CSMOM.m<-sign.CSMOM.m[period]

#save number of held contracts
CSMOM.ex.ret.m<-abs(sign(sign.CSMOM.m))
CSMOM.ex.ret.m<-CSMOM.ex.ret.m[period]

CSMOM.m<-lag(as.xts(1/rowSums(CSMOM.ex.ret.m,na.rm=T)*rowSums(sign.
    CSMOM.m*lag.agg.ret.m*vol.target/sqrt(agg.vol.m),na.rm=T),order.by
    =index(agg.ret.m)),1)
```

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Zhou, G. and Zhu, Y. A theory of technical trading using moving averages. *Working paper*, 2014.

Hannes Kusstatscher, BSc

education

2013–2016 University of Vienna

Masters of Quantitative Economics, Management and Finance

Specialization in Finance
Description: The aim of the masters degree program Quantitative Economics, Management and Finance at the University of Vienna is to impart to the students the knowledge and skills required to analyze business, economics and statistics issues using mathematical models and to apply mathematical methods in the fields of business, economics and statistics.

2012–2015 University of Vienna

Bachelor of Mathematics (unfinished)

Description: The bachelor degree in Mathematics provides students with the basic knowledge of various fields of mathematics.

2009–2013 Vienna University of Economics and Business

Bachelor of Business, Economics and Social Sciences

Specialization in Economics
Description: The bachelor program in Economics provides students with knowledge in the main fields of economics and the skills to apply important economic methods.

work experience

2015–Present Associate, Financial Services Advisory

KPMG Alpen-Treuhand GmbH

Consulting of Austrian and international banks with a focus on IFRS 9 Impairment Methodology and various other topics from risk regulatory.

2014–2015 Research Assistant, Research Institute for Capital Markets

Vienna University of Economics and Business

Quantitative Implementation of investment strategies in R Statistics and market research as well as tutoring and administrative support for the Portfolio Management Program.

2014–2015 Freelancer, Balance Sheet Risk Management

Raiffeisen Bank International

Harmonization of market data between RBI Head Office and network units and process optimization.

2014 Full-Time Intern, Balance Sheet Risk Management

Raiffeisen Bank International

Preparation of market data for the end-of-day evaluation, market conformity verification and supervision of various portfolio limits.

2012 Intern, Bressanone – Italy

Südtiroler Sparkasse

Assistant of the branch manager, various projects.

OTHER EXPERIENCE

2013–2014 Portfolio Manager, PORTFOLIO MANAGEMENT PROGRAM

Vienna University of Economics and Business

Managing a portfolio with €1.2 Mio assets under management and presentation of investment strategies.

2012–2013 Portfolio Analyst, PORTFOLIO MANAGEMENT PROGRAM

Vienna University of Economics and Business

Support for the Portfolio Managers regarding quantitative and qualitative investment decisions, risk management.

COMPUTER SKILLS

Advanced Windows, Linux, Microsoft Office, Libre Office, LaTeX, Bloomberg, Thomson Reuters & Datastream, R-Statistics incl. RBloomberg, VBA, SAS

Intermediate MATLAB, E-Views, SQL

Basic Java, Python, Batch, SPSS

OTHER INFORMATION

Volunteering

2007–2015 · Member of the youth council in the city of Chiusa, Italy

2006–Present · Active member of the South Tyrolean Alpine Association

Languages

GERMAN · Native speaker

ENGLISH · Fluent

ITALIAN · Fluent

ROMANIAN · Basic

SPANISH · Basic