School of Economics and Management

Master Thesis

Time-series Momentum across asset classes: a case study on momentum strategy with focus on illiquidity and market crashes.

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Abstract

This study re-examines the time series momentum strategy across asset classes by Moskowitz et al. (2012) framework with the focus on illiquidity and market turning points. The results in this research suggest that over the sample period from August 1994 till September 2019 there are positive trends in the shorter time horizon as the initial paper concluded. The time series momentum strategy based on lookback period of 12-month and one-month holding period is the most profitable. The strategy generates positive returns for equity and the bond classes. However, the commodity class shows no significant abnormal returns. The study finds no relationship with cross-section and time-varying illiquidity measures. In comparison with the passive long investment strategy, the time series momentum strategy over performs the strategy. Remarkable is that the difference between the strategies is very significant during the financial crisis. On the other hand, the portfolio constructed by the time series momentum strategy is less diversified than the passive long investment strategy.

1. Introduction

Momentum is a dynamic where an asset maintains their current trend in the future. An asset that recently increased is more likely to continue moving higher, and an asset that recently declined is more likely to go lower. The momentum strategy takes an advantage of this concept. Momentum is well-researched and De Bondt and Thaler (1985, 1987) is one of the early papers that writes about it. Many of the momentum studies are based on cross sectional data: Jegadeesh and Titman (1993), Asness (1995) and Pirrong (2005). However, Moskowitz et al. (2012) introduced time series momentum where the strategy is based on the absolute strength rather than relative strength of an instrument. Bird, Gao and Yeung (2017) even suggest that momentum using time-series is superior to momentum found by cross-sectional data. They claim that even both strategies generate positive returns the difference lies in the market conditions. Since, during extreme markets conditions it is harder for the cross-sectional momentum to obtain information about winning and losing stocks. The time series momentum does a better job since it looks specific to an instrument own past return. Another interesting paper is that of Avramov et al. (2013). They claim that the profitability of time series momentum varies with the state of the market illiquidity and that the factor is driven by illiquidity. The evidence they show is the behavioural theory which states that the overconfidence of investors triggers trend continuation. Subsequently, illiquidity is linked with overconfidence since during illiquid periods the overconfidence is low because of high trading cost. To determine whether momentum is a coincidence finding in US stock market, a behaviour related to the investor's bias or duo methodology flaws, it needs to be challenged. Therefore, I investigated time series momentum across different asset classes which are equity, bond and the commodity class by using Moskowitz et al. (2012) framework. The research question is formulated as "*Does time-series momentum exist across different asset classes after appropriately controlling for risks, illiquidity and market turning points?*"

This study about time series momentum contributes in three ways. Firstly, it contributes to the behaviour studies and disapprove momentum as a coincidence. Secondly, this study shows individuals that a simple asset allocation based on momentum strategies can improve their portfolio return. Since the common advice given to non-professional investors is to hold a diversified portfolio based on the global market with risky assets like stocks and some low-risk assets like bonds to compensate returns during market crashes. This is also called passive investing. Nevertheless, there are some shortcoming to passive investing that critics pointed out like limited returns, overvalued assets and no anticipation to economic cycles. The perception of blindly holding a portfolio based on the market weight can therefore be questioned. Thirdly, this study re-examines the statistical and economical evidence of Moskowitz et al. (2012).

This study first starts by examining the randomness in return data of 42 instrument since the time series momentum strategy profits from the trends in returns. The randomness analysis provides simple understanding about the return continuation of the entire sample period which are the monthly returns of the last 25 years. Next, by back testing different time series momentum strategies over the entire sample period, I obtained the best performing time series momentum strategy. The analysis that follow are based on the obtained time series momentum strategy. Hereafter, I go more in-depth by using this strategy. First, I examined the performances of the time series momentum strategy for each individual instrument. The performances are compared with each other by calculating the Sharpe ratios for every instrument. Second, I examined if the time series momentum strategy is driven by illiquidity. By calculating the illiquidity score for every instrument based on the normalization of the ranks of their daily volumes. I tested the correlation between the Sharpe ratios and illiquidity scores. Another test I performed for illiquidity is by using two time-varying liquidity proxies the TED-spread and VIX index and confirm whether it has explanatory power to the time series momentum. Third, I examined the time series momentum over time in order to understand the performance of time series momentum during different market states. Therefore, I analysed when two popular financial crashes occur: The Dot.com Bubble and the Global Financial Crisis. In this study I often compared the time series momentum strategy against another popular investment strategy which is the passive long investment strategy. So, I compared the relative performances of the strategy against the passive investment strategy. Afterwards, the time series momentum returns are tested against the squared World index to see if there is significant difference in returns during market downfall. Finally, I examined the correlation structure of the portfolio that is constructed using the time series momentum strategy. The correlations of the asset classes are compared to the portfolio of the passive investment strategy. The correlation structure is important for investors since it is necessary to diversify instruments across asset classes to minimize the portfolio risk.

2. Literature review

2.1 Market efficiency hypothesis

In finance there is a large discussion if markets are efficient. This believe became more recognised after Eugene Fama published his research about the Efficient Market Hypothesis (EMH) in 1970. In this research Fama categorises three market states. In the weak form it discusses information from historical data and concludes that future prices cannot be predicted from the past prices. Thus, trading strategies based on historical prices are not applicable. It also suggests that the prices are not always the fair value, but it is simply impossible to make systematic profits. Although, some fundamental analysis may provide some abnormal returns in the weak market state. So, if future prices are not based on past price series, they must follow random price movements. The efficient market hypothesis is therefore related to the random walk theory. In the semi-strong efficiency form the paper discusses market efficiency where new information is quickly publicly available or in a bias way. This efficiency form concludes that neither fundamental analysis nor technical analysis will provide abnormal excess return. In the final strong form, it concludes that market prices are fully reflected by all information whether public or private. In other words, in this state it is impossible to beat the market since it assumes that any information is processed immediately. However, there might be deviations to the EMH and the market states. Empirical studies show that there are markets which are not efficient and strong theories suggest that financial assets are prices by fundamental risk factors. For example, Fama and French (2015a) identifies five common risk factors on stocks and bonds markets. Another example are the findings of Asness, Moskowitz, and Pedersen (2012). They find substantial value and momentum premiums in eight different markets and asset classes. These studies believe that returns are compensation for risk and therefore investors are looking for risk premiums to beat the market. Fama refers momentum as the biggest challenge to market efficiency.[1] Momentum is a dynamic where an asset maintains their current trend in the future. An asset that recently increased is more likely to continue moving higher, and an asset that recently declined is more likely to go lower. This effect is in contrast and violates the efficient market hypothesis which states that the past prices cannot predict future prices. The momentum strategy takes an advantage of this concept. However, there are two practical problems. The first drawdown is that the strategy suffers during market turning points or

[1] 1See, for example, *http://www.nobelprize.org/nobel prizes/economic-sciences/laureates/ 2013/fama-lecture.html* for Eugene Fama's Nobel Prize lecture.

when trend reversals occur. Second, the selection with the strongest trend changes all the time causing high turnover in the portfolio of the strategy. Because of the high turnover in the portfolio, the transaction cost become enormous and reduces the momentum premium.

2.2 Momentum

The momentum effect in the literature provides evidence against the weak form of market efficiency hypothesis. Jegadeesh and Titman (1993) explains momentum by "The momentum strategy buys instruments that performed well in the past and sells instruments that performed poorly". A similar strategy is called contrarian strategy where investors do the opposite of this method. These strategies are based on the relative strength of the past stock prices which contradicts with EMF. De Bondt and Thaler (1985, 1987) proposed that this phenomenon is duo to investors tend to overreact to information. When investors overreact to news, the price tend to go further than its fair value. The direction of the extension depends whether it is a positive or negative news. There evidence is the mean reversion that occurs in the past stock prices. Mean reversion is the assumption that stock price will move to his average price in the long run. This pattern makes the stock prices predicable and causes trading opportunities. The paper tests both contrarian and momentum strategies and find contrarian strategy more profitable in the long run. Some papers, for example Chan (1988) and Ball and Kothai (1989), discuss that this is due to their systematic risk. When investors obtain abnormal returns, it is likely that it is just a normal compensation because there is a shift in risk during the long period. Jegadeesh and Titman (1993) investigated the momentum strategies further after these suggestions and made it more confusing. In contrast with the previous paper, it suggests that the abnormal returns of relative strength strategies are not due to their systematic risk. The paper also finds significant positive returns for momentum rather than contrarian when holding portfolios between three to 12-months. Another evidence they show is that momentum is positive for the short term and negative for the longer time horizon. Therefore, they suggest that the current explanations of these effect over- and under reaction are too simplistic. In his earlier work, Jegadeesh (1990) shows evidence for shorter-term return reversals and suggest this may occur by lack of liquidity rather than overreaction. So, this may explain the contrarian success which was found earlier since it is also transaction intensive. Asness (1995) also examined the momentum effect in equity markets for short-term and long-term. It confirms that past returns have significant power to explain future returns. This is more evidence against the efficient market hypothesis. The paper also concludes that 12-month momentum strategy has explanatory power for stock returns. A research outside the equity market about momentum is from Pirrong (2005). He investigated momentum in the future markets and finds that it indeed exists even adjusting for risk using parametric and non-parametric model. The paper uses two parametric models': capital asset pricing model (CAPM) and the Fama-French three factor model for risk adjustment. Fama-French variables were also used by Asness (1995) for risk adjustments. However, the results suggest that momentum and reversals are pervasive phenomena that cannot explained by asset pricing models and further research is needed. The findings in the literature can be divided into two groups. The first group says that the findings about momentum are duo to methodological flaws like poor risk control and transaction cost. And a second group that argues that momentum exists due to irrational behaviour of investors like under- and overreacting to information.

Lately, there are some researches where momentum and value premiums are investigated jointly and across asset classes. Asness, Moskowitz, and Pedersen (2012) showed new insights about momentum and value premiums. The paper shows significant abnormal return for value and momentum for each class. They also find correlation between the returns across asset classes. Momentum is positively correlated with momentum across unrelated markets and suggest a global factor related to momentum. Next, it examines the economic drivers of the premiums and their correlation. The only significance they find is the correlation between liquidity and the premiums across markets. Value premium is negatively correlated, and momentum is positively correlated with liquidity risk. The positive relationship of liquidity and momentum is suggested earlier by Pastor and Stambaugh (2003) and Sadka (2006) but only for the U.S individual stocks. Similar researches to this are from Blitz and van Vliet (2008) and Haghani and Dewey (2016). Haghani and Dewey (2016) finds abnormal returns compared to static investment strategies using simple measurements for value and momentum. Also, they find higher abnormal returns when combining the two factors value and momentum than using them alone. Blitz and van Vliet (2008) main finding also confirms that there is statically and economically significant abnormal returns for value and momentum.

3. Hypothesis

In the interest of investors, as relevant to researchers and in order to obtain my master degree, I investigated time-series momentum. Since, it is beneficial to diversify across asset class, I investigated momentum not only in one specific class but also across classes: equity, bond and commodity. This resulted in spreading the risk of investor's portfolio. The two common practical implications of time series momentum are illiquidity and market turning points. Thus, the main research question is formulated as the following:

Main Research Question: *"Does time-series momentum exist across different asset classes after appropriately controlling for risks, illiquidity and market turning points?"*

In order to do so, the first question that I had to answer was if there is any return continuation and reversal in the returns. This is because the momentum strategy takes benefits of these trends. Without any trend in the return data, it is not possible for the momentum strategy to gain any profit. The hypothesis for this research question is formulated as the following:

H0: There is no return continuation and reversal in instruments returns across time.

The hypothesis is tested by testing the autocorrelation of the returns with different lag periods. If there is any trend in the return data, the t-statistic of the intercept from the lag periods will indicate a positive t-statistic and a reversal if the intercept has a negative t-statistic. Next, I had to answer which momentum strategy performed the best. Since, the time series momentum strategy is based on a lookback period. I had to determine which lookback period is the most significant and how significant does it vary from the benchmark. In order to answer this, I formulated the following hypothesis:

H0: The time series momentum strategies do not outperform the passive exposure for each asset class and Fama- French factors.

I tested this hypothesis by comparing the various time series momentum strategies against the Fama-French benchmark. By estimating the intercept and varying the different lookback period in the strategy I obtained the best performing time series momentum strategy. After obtaining the best momentum strategy, I go more in-depth with two common practical implications the momentum strategy has. The first implication is if momentum is driven by illiquidity. If time series momentum is correlated with liquidity, it means that the profitability will be reduced in illiquid markets. Subsequently, the results will be in favour of investor behavioural theory which suggested that illiquidity is linked to overconfidence and overconfidence of investor's triggers continuation. Therefore, I tested if the time series momentum returns are driven by the illiquidity. Since, illiquidity can be measured cross-sectional and time-varying I formulated two hypotheses. The hypothesis formulated for cross-sectional illiquidity is:

H0: There is no relationship between the performance of the time series momentum strategy and illiquidity in the cross-section.

This hypothesis I tested by calculating the correlation of the illiquidity of each instrument and the Sharpe ratio of each instruments. The hypothesis formulated for time-varying illiquidity is:

H0: There is no relationship between the performance of the time series momentum strategy and time varying liquidity.

This hypothesis I tested by regressing the time series momentum return against two time-varying liquidity proxies. The significance of the variable shows if they have explanatory power to the strategy which suggest that the strategy is driven by illiquidity. The second implication of the time series momentum strategy is the influence of the market circumstances. The question here is: how well does time series momentums strategy perform during market turning points? If the momentum strategy fails to gain profits during these periods, it would suggest that the momentum strategy failed to identify the reversal. Therefore, I tested how the extreme market circumstances influence the time series momentum strategy. The hypothesis is formulated as the following:

H0: There is no positive relationship between the returns of the time series momentum strategy and extreme markets states.

This hypothesis is tested by regressing the time series momentum returns against the MSCI world index and the MSCI index squared. If the squared returns of MSCI index has explanatory power to the time series momentum returns this will indicate that the strategy has significant profits during market crashes. Additionally, I answered this hypothesis by examining the growth of the time series momentum return over time and focusing on the time period of the markets crashes explicit. In the end, I investigated the correlation structure to understand the relationship between momentum and the returns across asset classes. Therefore, the last hypothesis is formulated as following:

H0: There is less correlation in time series momentum strategy than the passive investment strategy.

I examined the correlation of the strategies with two different measures. First, I calculated the average pair-wise correlation within an asset class. Second, I calculated the correlation of the strategy across asset classes. By using two different points of view, it provides a better understanding about how to instruments are constructed. Both results are compared to the passive investment strategy.

4. Data

4.1 Variable description & sample selection

For this study, I take into consideration a set of criteria when not to include an asset class. First, I excluded emerging debt and hedge funds since there is less data available. Second, I excluded currencies since this asset class has high volatility compared to the others and it is considerably difficult to model. Third, I excluded illiquid markets like the real estate and private equity.

For this research I used data from three major asset classes: equity, bonds and commodities. To avoid illiquidity, I focus on the most liquid instruments available on the market for those three asset classes. I used similar dataset as Moskowitz et al. (2012) but with some changes in bond class. I categorized the equity and bond classes on country level to obtain a global portfolio. I selected the same government bond indexes as the countries used for equity classes. Therefore, the dataset contains seven developed equity indexes, seven developed government bonds indexes with three years and ten years maturity and 21 commodities. The dataset period is from August 1994 to September 2019 to ensure that all assets have data and the dataset period is long enough. The data is categorized on country level and the assets are spread around the world.

Equity index (7): SPI 200 (Australia), CAC 40 (France), DAX (Germany), TOPIX (Japan), AEX (Netherlands), FTSE 100 (UK) and S&P 500 (U.S).

Bond index (7): I obtain the 3-year and the 10-year government bonds for the same countries as equity. Australia, France, Germany, Japan, Netherlands, U.K., and U.S.

Commodity index (21): Aluminium, Copper, Nickel, Zinc are from London Metal Exchange (LME), Brent Crude, Gas Oil, Cotton, Coffee, Cocoa, Sugar are from Intercontinental Exchange (ICE), Live Cattle, Lean Hogs are from Chicago Mercantile Exchange (CME), Corn, Soybeans, Soy Meal, Soy Oil, Wheat are from Chicago Board of Trade (CBOT), Natural Gas are from New York Mercantile Exchange (NYMEX), Gold, Silver are from New York Commodities Exchange (COMEX), and Platinum from Tokyo Commodity Exchange (TOCOM).

The data for all instruments are total returns index which includes dividends for stocks and coupons for bonds. [2] Traditionally, simple returns are calculated from the total return index with the following formula:

$$R_t = \frac{TRI_t}{TRI_{t-1}} - 1 \qquad (1)$$

Where:
TRI_t= Total return index at time t
R_t = Simple return at time t

Next, I obtain the one-month T-bill interest rate from DataStream. I subtracted the one-month T-bill from the simple returns to obtain the monthly excess returns. In this study I used the one-month T-bill as a proxy for the risk-free rate. Finally, in order to obtain log return or compounded returns I converted the simple monthly excess returns with the following formula:

$$r_t^e = \ln(R_t^e + 1) \qquad (2)$$

Where:
r_t^e = Log excess return at time t
R_t^e = Simple excess return at time t

The compounded monthly excess returns are a proxy for the returns that an investor can obtain with future contracts. It is important that the index returns are similar to the future contracts because when an investor wants to invest, they pay the price of a future contract and not the index price.

4.2 Benchmarks & Proxies

In this paper I discussed the results by comparing the return series to standard asset pricing benchmarks. Since, I examined three major asset classes, I selected a benchmark for each asset class. For equities I used the MSCI World equity index as benchmark since it is used as a common benchmark for the world. A popular benchmark for the bond market is the Barclays Global Aggregate Bond Index and for commodities is the S&P GSCI Index (GSCI).

Additionally, in this paper I also compare the abnormal returns with popular risk factors. The most common risk factors are the standard Fama-French factors with the market factors: SMB, HML, and UMD. The model captures the risk premium for size, value and cross-sectional momentum. The Fama-French factors SMB, HML, and UMD are available on the website of Kenneth R. French. For in-depth analysis of the momentum strategy I compared

[2] Welch & Goyal (2008) also include dividend in the return since this is the total rate of return for equity premium.

the results with another similar study. The study from Asness, Moskowitz, and Pedersen (2010). Their research examines the value and cross-sectional momentum factors across asset classes which I used as another proxy to evaluate the results. The factors can be found on Lasse H. Pedersen's website. Additional in-depth analysis is performed for illiquidity. For this part I needed three proxies. The first dataset is cross-sectional data where I used a snapshot of the recent daily trading volume for ranking the instruments illiquidity which is available on Yahoo finance. The second and third proxies are time-varying proxies. For this part I used the TED Spread. The TED spread is also known as the difference between LIBOR and T-bill at three-month maturity. The TED spread is available on the website of Federal Reserve Bank of St. Louis. Finally, I used the historical VIX index as another proxy which can be obtained from CBOE's (Chicago Board Options Exchange) website. Both proxies are also used in the research of Moskowitz et al. (2012). The paper used these proxies after Brunnermeier and Pedersen (2009) suggested that market liquidity is correlated with volatility. The evidence they have is that trading in more volatile instruments requires margin payments. On the other hand, illiquidity per margin is kept constant by speculators and therefore the liquidity co-moves with volatility.

4.3 Preliminaries

Before beginning any empirical analysis, a preliminary statistics analysis is performed on the dataset. There are several important conditions the dataset needs to hold for using it with time series analyses and use the ordinary least squares method. One of the most important criteria is that the data needs to be stationary. This means that the distribution of errors does not change over time. Non-stationary data are hard to model since there mean and variance change over time. This is also called unit root. The problem with unit root is that I cannot do hypothesis testing and the T-statistics does not have a standard normal distribution. The presence of unit root in data can be tested through an Augmented Dickey-Fuller (ADF). Price series are usually time dependent which means that tomorrow's price is based on today's price. Since the price is a time dependent variable and it violates key assumption of performing empirical analysis, it needs to convert before applying. Taking the first difference of prices and convert it into returns solves this problem. Therefore, I used return series rather than prices which are obtained directly from DataStream to avoid this problem. The results of the ADF tests on the return series are demonstrated in the second column of Table 1. The results show that the t-statistics are clear enough to reject the null-hypotheses on a 1% level for each instrument. Thus, the monthly excess log return series are stationary, and the problem of non-stationarity is fixed.

Another key assumption for OLS is that the errors of the model needs to be uncorrelated with each other in different time periods for any value of the explanatory variable, see the formula below:

$$Corr(\varepsilon_t, \varepsilon_i | X) = 0 \qquad (3)$$

Where:
ε_t = The error at time t
X = Explanatory variable of the model
i ≠ t

Serial correlation has two negative consequences which are inefficiency and inconsistency of the estimated coefficient. Therefore, for all the regression models in paragraph methodology I preliminary tested the errors ε_t for serial correlation by using Breusch-Godfrey Test. On the other hand, in time series I also rely on homoscedasticity this means that the variance of error ε_t is constant and finite for any value of explanatory variable at the same time period. If this assumption does not hold the standard errors will not be valid anymore.

$$Var(\varepsilon_t | X) = \sigma^2 \qquad (4)$$

This is tested using the Breusch-Pagan Test which has three steps. The first step was to estimate the regression. Second, I obtained the residuals and square them $\hat{\varepsilon}_t^2$ and estimate the following regression:

$$\hat{\varepsilon}_t^2 = \gamma_0 + \gamma_1 X_t + e_t \qquad (5)$$

$\hat{\varepsilon}_t^2$ = Estimated residuals at time t
γ_1 = Estimation coefficient of variable X
γ_0 = Intercept

Finally, I used F-test to test the null hypothesis of homoscedasticity. If I cannot reject the null hypothesis it means that I have not enough evidence to assume heteroscedasticity which makes the coefficient estimated bias.

4.4 Summary statistics

Table 2 presents summary statistics of the excess log returns on the instrument's indexes. The table summarizes the numbers of observations, mean (annualized), standard deviation (annualized), the minimum, median, maximum, the skewness and the kurtosis of the dataset for each of the instrument. The table also splits the instruments by asset classes. The first column shows the number of observations is 302 which states that there are 302 monthly returns from August 1994 till September 2019. The second and third columns are the time

Table 2

Descriptive Statistics

Summary statistics on the return series. In this table are reported mean return (annualized) and standard deviation (annualized) of each instrument's indexes sample from August 1994 to December 2019. Also, the monthly minimum, median, maximum, skewness and kurtosis values of the sample are reported. As the table shows, there are 3 categories which are Equity (1), Bond (2) and Commodities (3).

Instruments	N	Mean	Std. Dev.	Min	Median	Max	Skewness	Kurtosis
AUS	302	6,36%	13,27%	-13,05%	1,07%	11,05%	-0,6368	3,6673
FR	302	5,04%	17,94%	-18,66%	1,02%	11,98%	-0,6431	3,7083
JAP	302	-0,84%	18,57%	-25,16%	0,38%	14,44%	-0,4865	4,0291
NL	302	6,12%	18,74%	-25,09%	1,23%	12,89%	-1,1207	5,4565
UK	302	4,44%	13,82%	-14,92%	0,87%	11,74%	-0,709	4,1557
USA	302	7,08%	15,93%	-18,63%	1,18%	14,66%	-0,8665	5,0149
GER	302	4,68%	20,92%	-22,95%	0,86%	17,99%	-0,756	4,6152
AUS3y	302	3,24%	2,53%	-1,47%	0,23%	2,96%	0,6295	3,9735
FR3y	302	1,44%	1,97%	-1,49%	0,09%	1,91%	0,1421	3,2052
JAP3y	302	-1,20%	1,39%	-2,06%	-0,05%	2,44%	0,5475	13,3835
NL3y	302	1,32%	1,94%	-1,54%	0,09%	1,87%	0,1274	3,4303
UK3y	302	2,40%	2,04%	-1,46%	0,19%	2,29%	0,2863	3,7678
USA3y	302	1,80%	2,36%	-1,90%	0,10%	2,41%	0,3251	4,0756
GER3y	302	1,20%	1,97%	-1,56%	0,09%	2,14%	0,4231	3,9623
AUS10y	302	5,52%	6,65%	-4,72%	0,41%	7,15%	0,1916	3,1575
FR10y	302	4,32%	5,75%	-4,06%	0,46%	6,53%	-0,056	3,3237
JAP10y	302	1,20%	4,30%	-6,18%	0,13%	6,30%	-0,0859	8,5964
NL10y	302	4,20%	5,75%	-4,36%	0,52%	6,58%	0,0173	3,636
UK10y	302	4,56%	6,24%	-4,85%	0,47%	6,50%	0	3,442
USA10y	302	3,12%	7,17%	-6,72%	0,31%	10,85%	0,3153	5,1256
GER10y	302	3,84%	5,61%	-3,71%	0,56%	5,51%	-0,0828	2,9051
Aluminum	302	-3,24%	19,30%	-36,99%	-0,43%	22,39%	-0,5112	10,0435
Copper	302	1,08%	25,11%	-41,11%	-0,47%	22,87%	-0,5911	7,1172
Nickel	302	1,80%	34,61%	-29,86%	-0,40%	27,80%	-0,1435	3,0152
Zinc	302	1,20%	25,91%	-36,89%	-0,24%	23,13%	-0,2574	5,1288
Brent Crude Oil	302	2,16%	32,18%	-45,63%	0,66%	31,30%	-0,5922	4,806
GasOil	302	2,64%	31,77%	-35,38%	0,76%	28,06%	-0,4374	4,0729
Cotton	302	-2,88%	29,90%	-43,84%	0,05%	27,66%	-0,4567	5,6754
Coffee	302	-5,28%	35,61%	-37,63%	-1,40%	35,27%	0,2581	3,6736
Cocoa	302	-0,36%	29,69%	-26,45%	-0,06%	32,29%	0,1173	3,6987
Sugar	302	-1,92%	33,12%	-28,75%	-0,02%	29,03%	-0,0962	3,3419
Live Cattle	302	-0,72%	17,46%	-24,27%	0,18%	11,40%	-0,7075	5,276
Lean Hogs	302	-0,36%	35,51%	-38,41%	0,07%	36,07%	-0,0854	4,6116
Corn	302	0,00%	29,79%	-40,80%	0,40%	22,77%	-0,7112	5,0906
Soybeans	302	-0,60%	27,02%	-44,69%	0,49%	19,30%	-0,91	6,4775
Wheat	302	-0,72%	29,41%	-23,09%	-0,33%	32,72%	0,1716	3,6553
Soy Oil	302	-1,56%	25,36%	-30,83%	-0,18%	26,79%	-0,2913	4,7844
Soymeal	302	-0,24%	31,59%	-47,49%	0,38%	24,25%	-0,5981	5,8252
Natural Gas	302	-1,56%	49,71%	-43,50%	-0,81%	45,93%	0,0533	3,5267
Gold	302	3,00%	16,21%	-19,66%	-0,22%	17,41%	0,0693	4,2823
Silver	302	2,28%	29,38%	-30,43%	-0,07%	23,10%	-0,2439	4,064
Platinum	302	0,96%	23,04%	-37,27%	0,16%	20,08%	-1,1984	8,8069

series mean and standard deviation for each instrument. To get a better view on the mean and volatility of the instrument I calculated the annualized values which is used more often. In order to calculate the arithmetic mean, I multiplied the average monthly excess log returns of the sample period by 12 months. On the other hand, by multiplying the monthly volatility with the square root of 12, I obtained the annualized volatility. The fourth column shows the minimum which indicated the lowest monthly return for each instrument. In contrast the maximum in the sixth column shows the highest monthly return for each instrument. The fifth column is the median which is less affected by outliners than the mean and can be a better indicator. Therefore, it is important to compare these two values. The mean in Table 2 shows that the mean returns across asset classes are significant different. There returns of the equity and bond class are mainly positive values while various commodity excess returns are close to zero or negative. As the volatility in Table 2 highlights, the annual volatilities for equity instruments are between 13-21%. The bond market has very low volatilities. This is expected since bonds are less risky than the other two asset classes. This is because the issuer of bonds are governments which will go hardly bankrupt. The volatility for 3-years bonds are approximately 2%. The 10-years bonds are slightly higher and have values around 5-6%. This implies that the longer the maturity is, the more volatile instruments become. This is also expected since the further we try to predict the future; it gets more unpredictable and complex. The volatilities of commodity instruments are the highest of the three asset classes which is expected. The lowest volatility of the 21 instrument is 17.46% and the highest 49.71%. Therefore, I can conclude that there is significant variation in volatilities for the commodities class. This is also expected since the prices can fluctuate enormous due to supply and demand. The last two columns show the skewness and kurtosis which are measures for data shapes. Skewness tells us if the data is symmetric. If the value is zero, the data is symmetric and therefore likely normal distributed. A negative number indicates that the data is skewed to the left and a positive number means it is skewed to the right. The skewness for all instruments is close to zero which is good. Only the stock market in the Netherlands and Platinum have slightly lower value than -1. Additional most of the instruments apart from bonds are skewed to the left since the values are negative. Kurtosis is a measure about the distribution of the tails. Data can be distributed with a heavy tail or light tail. A value greater than 3 indicates a heavy tailed distribution and values lower than 3 light tailed distribution. The values of the instruments are all greater than 3. Therefore, extreme returns are likelier to occur. Especially for Japan's government bond and for aluminium and platinum. The monthly returns I collected are close to a normal distribution.

5. Methodology

5.1 Time series momentum

One of the main differences between cross-sectional and time series data is that there is time as natural order in the data. This means that there may exhibit trends and seasonality in the dataset. The concept of time series momentum strategy depends on the instruments trending for a constant period. So, in this study we already test for the trends in the time series data. Time series analysis is used to understand the past observations and to forecast the future. In the literature there are various models to perform a time series analysis: Moving Average MA (q), Autoregressive model AR (q) and the combination of both Auto Regression Moving Average model ARMA (p, q). Moskowitz et al. (2012) introduces a very simple framework for time series momentum. First, it investigates future returns by using two similar AR (1) models which are a parametric model by only focusing on instruments own past return. The model examines trends and reversals for across asset class and for each asset classes separately. By using this model, I tested if there is any return continuation and reversals across different time horizons. Hereby, I indirectly test the market efficiency since I test if past instrument returns help predict current instrument returns. The first regression from equation (6) uses the size of the lag return and the second equation (8) uses the sign of the lag return. The excess return r_t^s for each instrument is regressed on the instruments own lagged return. This is repeated for every instrument with various lag periods. Before I regress, I scaled the excess returns with the lag of their ex ante volatility which is explained in detail in the next paragraph.

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \frac{\beta_h r_{t-h}^s}{\sigma_{t-h-1}^s} + \varepsilon_t^s \qquad (6)$$

Where:
r_t^s = Excess return for instrument s at time t
σ_{t-1}^s = Lagged ex ante volatility estimation
r_{t-h}^s = Excess return for instrument s at h lagged time.
σ_{t-h-1}^s= h lagged ex ante volatility estimation.
ε_t^s= The error for instrument s at time t
h = 1, 2 …60.

I also regressed the pooled panel regression using clustering by time since the observations are related to each other. So, I regressed the return at time t of all each instrument with 60 different lags h= 1, 2,… , 60 months which is 5 years. Afterwards, I repeated this progress for each separate asset class. The positive t-statistics of the intercept indicates return continuation or trends and a negative t-statistics indicates a reversal.

Their volatility differs intensely across instruments. Therefore, to make meaningful comparison between assets classes the volatilities of the instruments needed to be scaled. The model from equation (6) scales the return by their lagged ex ante volatilities. Moskowitz et al. (2012) says that it is the same as if using GLS instead of OLS. The benefit of GLS is that it is more robust than OLS and I do not need to test for serial correlation and heteroscedasticity in models. In the summary statistics it is mentioned that our instrument's volatilities also differ dramatically. Therefore, to make meaningful comparison between assets classes the volatilities of the instruments needed to be scaled. The first step is to calculate the ex-ante volatility σ_t for every instrument for each month. Volatility estimation is very important since the results depends on a reliable volatility forecast. Volatility is the magnitude of price changes and is known as risk in the finance. In the literature there are two approaches for computing volatility, one is the historical and the other approach is by using implied volatility. Implied volatility ignores the past and assumes that the market knows the best. When using historical volatility for volatility estimation I could use four popular methods which are explained in Poon and Granger (2003). The methods are called simple volatility calculation, moving average, exponentially weighted moving average (EWMA) and generalized autoregressive conditional heteroscedasticity (GARCH). The difference between the methods is applying weights. The simple volatility calculation is unweighted and assumes that all return series through time are equally weighted. EWMA improves on this method by giving greater weight to more recent returns and decline the weight over time because I am interested in volatility of the future. GARCH is similar to EWMA but takes a step further by adding a mean reversion. I want to use a model that is easy to implement with efficient result. Therefore, I choose EWMA rather than the GARCH model since is it simple to implement. Also, since EWMA is an improvement over the simple volatility calculation and moving average method by adding more weight to the recent returns I expect to obtain more realistic estimation. Guo (2012) estimates volatility by using EWMA model with the following simple formula:

$$\sigma_t^2 = \lambda \sigma_{t-1}^2 + (1-\lambda)\mu_{t-1}^2 \qquad (7)$$

Where:
λ = Smoothing parameter

σ_{t-1}^2 = One months lagged volatility
μ_{t-1}^2 = Squared lagged excess return
σ_t^2 = Ex ante volatility at time t

Where lambda is the degree of weighting decrease which is also called the smoothing parameter. A higher lambda indicates that the volatility will fall off slowly which means that the volatility persists. A lower lambda indicates that the volatility falls off rapidly and thus greater weights to the recent returns. If I take 1 as lambda that means that all volatilities in the series weight the same. The volatility at time t is denoted as σ_t^2 and indicates the historical volatility value. Finally, the exponentially weighted moving average of lagged monthly returns is denoted as μ_{t-1}^2. The ex-ante volatility is calculated the same for each instrument. Finally, I applied the ex-ante volatility at time $t-1$ with the returns at time-t to overcome look-ahead bias.

The second regression of the AR (1) model test the return continuation or trends by replacing the size of the return with the sign. This helps compare the results between the instruments. The second regression is formulated as the following:

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h sign(r_{t-h}^s) + \varepsilon_t^s \qquad (8)$$

Where:
r_t^s = Excess return for instrument s at time t
σ_{t-1}^s = Lagged ex ante volatility estimation
$sign(r_{t-h}^s)$= The sign of the h lagged return of the s instrument (-1 or +1)
ε_t^s= The error for instrument s at time t
h = 1, 2 …60.

Now that the continuation and trend reversals are analysed, I back test some trading strategies based on time series momentum. The parameters that varies in each strategy is the number of lookback periods and the holding periods. The lookback period gives the buy or short signal based on its sign. Additionally, Moskowitz et al. (2012) uses the volatility to size each position in each strategy. In the academic literature the most two common approach to weight stocks are to equally weight or to allocate based on the market weight. An important difference is that by equally weighting the portfolio will be tilted to smaller instruments. However, a third method is by allocating the fund by each instruments inverse volatility of the returns. This method is both used by Moskowitz et al. (2012) and Bird, Gao and Yeung (2016). This helps to stabilize the portfolios volatility since it is tilted to stocks with lower volatility. Otherwise, the strategy can be dominated by volatile periods. So, for each instrument for every time point, I checked if the excess return is positive or negative. When the return is positive, I buy the contract and go short when it is negative. The position size is based on the volatility as I mentioned earlier. This is the inverse of the ex-ante volatility $1/\sigma_{t-1}^{s}$, each month. The methodology which is also used by Jegadeesh and Titman (1993) derives a single time series monthly returns for each trading strategy. Each strategy has a look-back period k and the number of holding months h. The time series momentum strategy returns are called $r_t^{TSMOM(k,h)}$ .The TSMOM returns are calculated for every instrument based on the sign of the various lookback period. The maximum lookback period and holding period is 48 months which goes far as 4 years. Afterwards, I obtained for every instrument and for each lookback and holding period a single time series of monthly returns. Next, by collapsing the data I obtained the average return for every lookback period and holding period. Therefore, the $r_t^{TSMOM(k,h)}$ is averaged across all instruments. I repeated this progress to obtain the average for each separate asset class by only using the instrument within an asset class. Now that I have obtained the returns of the different momentum strategies, I compared the results to different benchmarks. In order to discuss the abnormal returns, their alpha is computed with the following regression.

$$r_t^{TSMOM(k,h)} = \alpha + \beta_1 MKT_t + \beta_2 BOND_t + \beta_3 GSCI_t + \mathrm{sSMB_t} + \mathrm{hHMLt} + \mathrm{mUMD_t} + \varepsilon_t \quad (9)$$

The regression controls for passive exposure to three major asset classes and Fama- French factors. MKT, BOND and GSCI are the proxies for the three major asset classes. SMB, HML and UMD are the risk factors from Fama-Fench.

5.2 In-depth analyse of time series momentum

By using the previous regression, I obtained the best performing momentum strategy with k number of lookback periods and h number of holding periods. The optimal strategy can differ for each asset classes. I obtained the best performing momentum strategy by focussing on all instruments combined. By using the returns of a single momentum strategy, I was able to analyse the strategy more in-depth. The more in-depth analysis started by examine each individual instrument, each separate class and all classes combined. Now that I obtained the best strategy, the following challenge is how to seize a portfolio. Moskowitz et al. (2012) sizes each position for every instrument so it has an ex ante volatility of 40%. The reason why they use 40% is because it is comparable to an average volatility of a security. After creating a portfolio with equally weighed instruments, the average return of the portfolio will have an annualized volatility of 12%. Therefore, I used the position size of $40\%/\sigma_{t-1}^{s}$, where σ_{t-1}^{s} is the ex-ante volatility of the instrument. I computed the return of each instrument and asset classes by using two time series momentum equations. The first equation computes the time series momentum return for each instrument at every time period:

$$r_{t+1}^{TSMOM,s} = sign(r_{t-12,t}^{s})\frac{40\%}{\sigma_t^s}r_{t+1}^{s} \quad (10)$$

The second formula calculates the return of the momentum strategy portfolio that diversifies across all 42 instruments S_t at time t.

$$r_{t+1}^{TSMOM,s} = \frac{1}{S}sign(r_{t-12,t}^{s})\frac{40\%}{\sigma_t^s}r_{t+1}^{s} \quad (11)$$

Where:
$r_{t+1}^{TSMOM,s}$ = Time series momentum strategy return for instrument s with one month holding period at time t
S = Amount of total instrument
$sign\left(r_{t-12,t}^{s}\right)$ = The sign of the cumulative return from the last 12 months (-1, +1)
σ_t^s = Ex ante volatility at time t
r_{t+1}^{s}= excess return of instrument s with one month holding period

Now that I computed the returns of each instrument and asset classes by using time series momentum, I compared the portfolios. Moskowitz et al. (2012) uses Sharpe ratios to compare the performances of portfolios. Sharpe ratio is a widely used method to calculate risk-adjusted return. Even though a portfolio can give a high return than the others. The best investment portfolios are those with higher returns which do not come with additional risk.

5.3 Risk exposure

The most common practical implications are controlling for risk, extreme markets and illiquidity. Since, I sized a new portfolio bases on 40% volatility portfolio by following the best performing momentum strategy, I compared the TSMOM returns once more against the passive exposure of the asset classes and the Fama-French factors. The returns are different now because of the positions. It could be interesting to see if the time series momentum is explained by SMB, HML and UMD. Particularly, the comparison between the time series momentum and cross-sectional momentum from the literature is interesting. Alternatively, the momentum strategy is compared to Asness, Moskowitz, and Pedersen (2010) factors for value and momentum everywhere. In contrast with this paper, they investigated momentum jointly with value premium.

5.4 Market turning points

Another practical implication is that the strategy is influenced during some period the markets crashes. Therefore, it is important to examine how the momentum strategy performs during these extreme periods. During the period from August 1994 till September 2019 which is the sample size there been two well-known market crashes. First, the Dotcom Bubble Burst which started from March 11, 2000, and lasted till October 9, 2004. Second, the 2007-2008 Global Financial Crisis which lasted till late 2010. Remarkable is that the latest financial crisis spread like a contagion to other economies and became a global crisis. Forbes and Rigobon (2000) explain contagion as a situation where the negative developments from one country or region affect healthy economies in other regions. Not only am I interested in the cross-country developments but also in the developments across asset classes. Since lately the financial markets are more linked to each other which increased efficiency and economic growth. However, this financial integration increased the systemic fragility as well which is explained by Acharya et al. (2009). By looking to the performances in returns over time and during the extreme market periods where the volatility level is high, I compared the results against the passive investment strategy which always goes long. In order to calculate the passive investment strategy, the sign in equation (11) is changed to 1. This is because the passive investment strategy goes always long. After computing the passive strategy, I compared the cumulative returns over the entire sample period with each other. The comparison is done in two ways. First, I compared the portfolio growth starting from €100 investment at the start of the sample period for both strategies. Second, I estimated the alphas for each instrument and for the diversified portfolio by regressing the returns of the strategy against each other. A higher alpha indicates that the time series strategy outperforms the passive investment strategy.

5.5 Illiquidity

The final practical implication I examined is illiquidity. Liquidity is a concept where investors can buy or sell any amount of security quickly without affecting the price. However, there are market frictions such as trading cost and rules that have an impact on the prices. Therefore, it is important to test whether the momentum strategy is correlated with illiquidity. In the literature there are different ways and methods to capture illiquidity. Amihud and Mendelson (1991b) even suggest that illiquidity cannot be captured by a single measurement. For example, Acharya and Pedersen (2005) estimate three type of liquidity in their paper. However, Moskowitz et al. (2012) provides a simple test to check whether his time series momentum is explained by cross-sectional illiquidity. First, it measures illiquidity through ranking each instrument by their recent daily trading volume within each asset class from highest to lowest. Next, it normalizes the ranks for each asset class with the simple normalization formula:

$$Score\ value = \frac{(Rank - \mu)}{\sigma} \qquad (12)$$

$Score\ value$ = The illiquidity scores
$Rank$ = The rank of the instrument within an asset class based on daily volume
μ = The average rank within an asset class
σ = The volatility of the ranks within an asset class

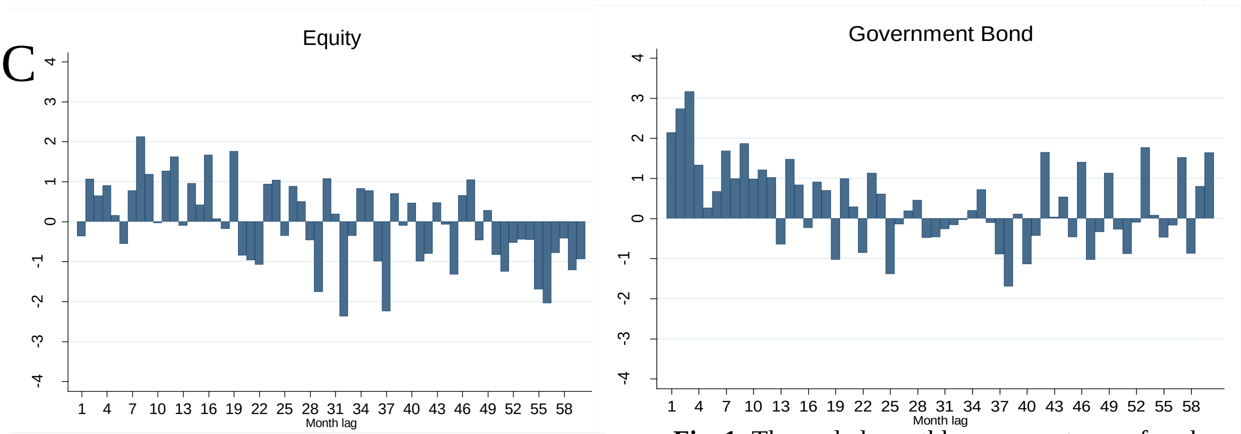
Where rank represents each ranked daily trading volume and μ is the mean of the volumes. Next, I divided the standard deviation from the ranks. This results in positive and negative values between -2 and 2. A positive value indicates more illiquidity and a negative value more liquidity within an asset class. Finally, I test for correlation between the performance of the time series momentum strategy (sharp ratio) and the illiquidity measures separately for each instrument and grouped together. Until recently, more studies focus on time varying liquidity. Therefore, in this paper I want to include two time-varying measurements. Moskowitz et al. (2012) uses TED spread as a proxy for funding liquidity. Another proxy the authors use, is the VIX index since the market volatility seems to relate to illiquid periods.

5.6 Passive investment strategy & correlation

I am also interested in the correlation structure of the time series momentum strategy and how it performs against a passive investment strategy. Moskowitz et al. (2012) investigates the correlation structure in two ways. The first way is by observing the average pair-wise correlation within an asset class for both strategies. The second way is by examine the correlation across asset classes for both strategies. Therefore, I first calculated the pair-wise correlation of the instruments returns among each asset class and average the results. So, this results in an average correlation within an asset class for each asset class. Next, I repeated this progress for the passive strategy. For the second method I calculated the diversified portfolio return within an asset class and compared the correlation of the three portfolios returns across asset classes. Afterwards, I repeated the progress for passive investment strategy.

6. Results

In Fig.1 Panel A are illustrated the t-statistics from the pooled panel regression for each lagged month across all asset classes. The panel shows that the longest trend continuation is at one-year time horizon, since the first 12 months are predominantly positive and mainly significant. After three months the trend loses its power but there is no significant reversal after this period. A reversal is indicated by a negative t-statistics. There is a strong reversal after 12 months and after two years. The results are in line with the finding from Moskowitz et al. (2012) but the results show that the magnitude of the trends are weaker, and the reversal is less strong.



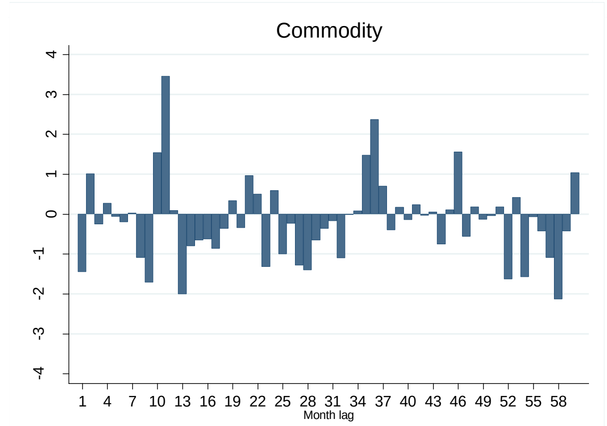


Fig. 1. The scaled monthly excess returns of each instrument are regressed on the instruments scaled lagged excess return. Panel A uses the magnitude of the lagged return as an estimator. Panel B uses the sign of the lagged excess return as an estimator. Panel C also uses the sign of the lagged return as an estimator, but the regressions are divided by asset classes. The graphs show the t-statistics of the pooled panel regression using clustering the standard errors by time (month). Sample period is August 1994 to September 2019.

The only difference between Panel A and B is the calculation. For Panel B I regressed by using the sign of the lagged return. The results from Panel B are very similar to Panel A, especially for the first 12 months but even stronger. The figure shows again predominately positive return continuation during that time and after the 12 months a strong reversal. The trend weakens after the first year and remains weak for the longer time periods. Here again, are the results in line with Moskowitz et al. (2012) findings. Panel C illustrate the results by asset class. The return continuation in the equity class is for the first two years positive but not very significant. Remarkable is that after four years there is significant strong reversal. In comparison to Moskowitz et al. (2012) findings, they show very positive trend continuation in the first year. Furthermore, their results show that after the second year the trend is predominantly negative. However, in my results the reversal is only obvious after four years. When looking to the bond class, the results show very significant trend in the first three months. This trend is positive till the 12th month but less substantial. The reversal occurs after 12 months. The positive trend becomes weaker after this time horizon. The results of Moskowitz et al. (2012) for bond class indicate that there is no substantial positive continuation in the first year but there is indeed a reversal after 12 months. However, I find positive trend continuation in the bond market. Finally, the commodity class shows no significant positive or negative trend during the first half year. After six months there is a short negative trend followed by very short and strong positive trend. After the first year there is a strong reversal and the trend remains negative for the following two year. The first year is in contrast with the finding of Moskowitz et al. (2012) since all months are positive and indicating positive trend. However, the months after the first year are very similar where the trend is mainly negative. To summarize, the results show that there is a positive trend for the first year but suggest that trends are stronger for a three months pattern. All results except for equity show a trend reversal after a year. Another important outcome is that there is a clear reversal after four years in the results apart from the government bond. The results are mostly in line with Moskowitz et al. (2012) findings but less strong and obvious. For instances, their t-statistic show a bit more significance. On the other hand, the bond and commodity class also show an opposite picture. This means that the pattern for these classes has changed over the recent years. In the end, based on the results of across all assets, equity and bond class. I can reject the null hypothesis which stated: There is no return continuation and reversal in instruments returns across time.

Table 3
In the table below are reported the coefficients and t-statistics from the time series regression of the momentum strategies with various lookback period on the following benchmarks: MSCI World Index, Barclays Aggregate Global Bond Index, S&P GSCI Index, HML, SMB and UMD. The first column shows the results for all asset classes, second column for equity, third column for bond, and fourth column for commodity. The final column shows how many observations are used in the regression.

	Intercept	Intercept	Intercept	Intercept	N
Lookback (months)	All assets	Equity	Bond	Commodity	
Lookback k=1	-0.084***	0.031	-0.278***	0.008	299
t-value	(-4.959)	(1.194)	(-6.552)	(0.349)	
Lookback k=3	0.097***	0.083*	0.244***	0.004	297
t-value	(4.773)	(1.818)	(6.866)	(0.190)	
Lookback k=6	0.090***	0.111***	0.222***	-0.006	294
t-value	(4.462)	(2.356)	(5.985)	(-0.282)	
Lookback k=9	0.076***	0.103***	0.229***	-0.035*	291
t-value	(4.278)	(2.424)	(6.394)	(-1.720)	
Lookback k=12	0.107***	0.099***	0.273***	-0.002	288
t-value	(5.609)	(2.219)	(7.526)	(-0.071)	
Lookback k=24	0.085***	0.078*	0.249***	-0.022	276
t-value	(4.332)	(1.658)	(6.524)	(-0.956)	
Lookback k=48	0.077***	0.040	0.250***	-0.026	252
t-value	(3.838)	(0.800)	(6.813)	(-0.964)	

T-statistics are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

Table 3 shows the coefficients and t-statistics from the time series regression of the momentum strategies which are constructed by different lookback periods. The different time series momentum strategy (TSMOM) is based on the lookback period which are suggested earlier in the return continuation outcomes. The previous test suggested that there is price continuation mainly in the first year. Therefore, I selected the lookback periods 1, 3, 6, 9, 12, 24 and 48 in order to view the time horizon. I evaluated the abnormal performance of the strategies by looking to the t-statistic of the estimated alpha which is the intercept of the regression. The coefficients of the risk factors are for now irrelevant for this part. The risk factors are tested and explained later during the in-depth analyse of TSMOM. The first column in table 3 shows that the alpha from the regression across all assets are very significant for all lookback periods. The highest significance for alpha across all assets is the strategy based on 12 months lookback period. The results are in line with the previous pooled panel regression and it confirms that the performance of the strategy for a one-year lookback is the strongest. The t-statistic from Moskowitz et al. (2012) are also all significant at 1% level. They also found that the 12-month is the most significant with a t-statistic of 6.61. In the following three columns are reported the results for each separate asset class. The second column shows the results for the time series momentum strategy used in equity class. The alphas in this asset class are less significant than the alphas across asset classes for all lookback periods. However, the months 6, 9 and 12 are still significant at a 1% level. The previous results of the pooled panel regression from testing return continuation indicated that the trend was not very significant for the first two years. The results in this column confirms that the trend is indeed weaker, but the abnormal performance is still very significant around half year and one-year time horizon. The results in this class are in line with Moskowitz et al. (2012). They find significance for the alpha with lookback period 6, 9, 12 and 24. There 9th lookback period is also the strongest with a t-statistic of 4.21 while the significance falls off after the 12th month time horizon. The third column shows the results from the bond class. The results are very significant for every lookback period. The strongest significant is for the lookback period with 12 months period. The return continuation test earlier also indicated that the bond market has very significant trend for periods shorter than a year or two. In the results there are some differences between Moskowitz et al. (2012). The t-statistic I obtained are much significant and the t-statistic after 12 years is still very significant. However, the strongest significant lookback period is still the 12th month lookback period. The fourth column shows the results in commodity class. Only the alpha of the momentum strategy with a nine months lookback period is significant on a 10% level. This result is very similar to the return continuation test since there was no significant trend during the first half year and only a short trend in the second half year. The momentum strategy underperformance here since the alpha is negative. In comparison with Moskowitz et al. (2012) the significant is different since their lookback periods are all significant for the first 2 years. This result was expected because the previous test already revealed no continuation pattern in the commodity class. To summarize all the columns in Table 3, the results are very similar as the previous test outcomes of return continuation. The momentum strategy shows a very significant abnormal performance using 12 months lookback period across asset classes. When I look to the specific asset classes, the momentum strategy performs well for the equity and bond market on a shorter time horizon especially for the 12 months period. On the other hand, I find no abnormal return for the commodity class for all lookback periods. The results are very similar to Moskowitz et al. (2012) findings. In particularly, the t-statistics from across all asset classes and equity class. In the end, the hypothesis I tried to answer was: The time series momentum strategies do not outperform the passive exposure for each asset class and Fama- French factors. Based on the results and t-statistic from Table 3, I can reject this null hypothesis mainly for all lookback periods at a 1% level for across all asset classes, equity and bond class. However, I can only reject this for the commodity class with a nine-month lookback period at a 10% significance level.

6.1 TSMOM in-depth analyse

In Fig.2 on the next page are reported the gross Sharpe ratio of the TSMOM for each instrument by using the best performing time series momentum strategy. The best performing momentum strategy is found in the previous test and is based on the 12-month lookback period and 1-month holding period. The Sharpe ratios are predominately positive and between the range of 0 and 1. The results show that the sharp ratios are the highest for the bond market, to be specific the 3-year government bonds and are approximately between 1.5 and 3. The bonds with longer maturity are lower with a Sharpe ratio of 1 which indicated that the average return is equal to its volatility. Remarkable is that the Sharpe ratio of Japan which was the highest for 3-year bond is sudden the lowest Sharpe ratio for the 10-year maturity bonds. The best performing equity index is the USA with approximately a Sharpe ratio of 1 and the least performing is the Australian index with 0.2. The commodity class has the lowest for Sharpe ratios of all asset classes. The highest Sharpe ratios in this asset class are the metal indexes which are Copper and Gold. The commodity class has also indexes with slightly negative Sharpe ratios which are Cocoa and Wheat. In comparison to Moskowitz et al. (2012) the Sharpe ratios for each instrument from equity show very similar statistics. However, the bonds in this study have very high Sharpe ratios. Also, this study suggest that the longer maturity bonds have lower Sharpe ratios. But, in their findings I cannot find any correlation that supports this suggestion. The Sharpe rations for commodity class are in this study very close to zero. In their study, they find higher Sharpe ratios for commodity class. This can be explained by the dataset since the previous tests already showed no patterns and abnormal returns in the commodity class.

6.2 TSMOM and illiquidity

In Fig.3 are the results of the illiquidity score for each instrument based on the daily trading volume. The figure illustrates the illiquidity of an instrument within an asset class. The highest score in the equity class has the Netherlands with its AEX index. This is expected since the market is small compared to the other countries and therefore traded less often. The lowest illiquidity score is from Japan with its TOPIX index. In the commodity class the most liquid instruments are Brent crude oil, Gold and Natural gas which are very popular indexes. When I test the correlation of the illiquidity scores and the Sharpe ratios of the previous results, I obtained a correlation value of 0.14. This indicates that there is a weak positive relationship between illiquidity and Sharpe ratios. Thus, the TSMOM strategy performs slightly better for illiquid instruments rather than liquid assets in the sample.

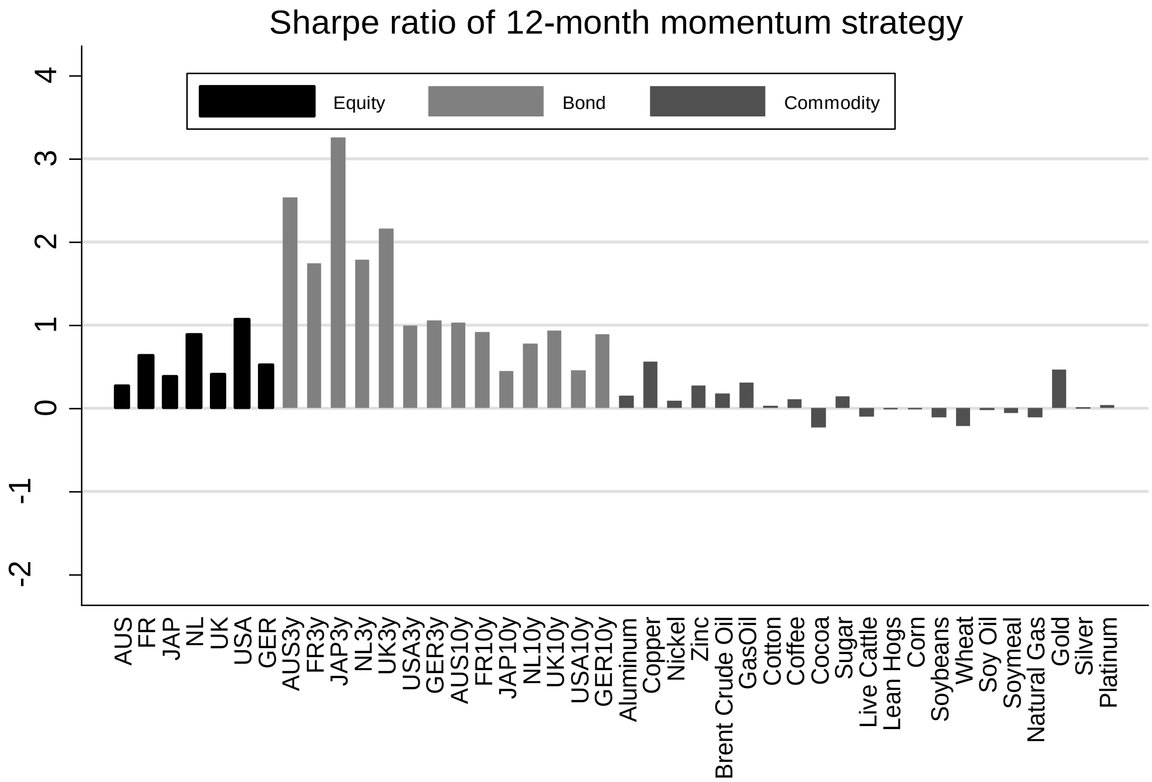


Fig. 2. In the figure are reported the gross Sharpe ratio of the 12-month time series momentum strategy for each instrument. The momentum strategy goes long or short based on the 12-month signal and the position is sized so that the annual volatility is 40%. The strategy is tested for the entire sample period from August 1994 till September 2019.

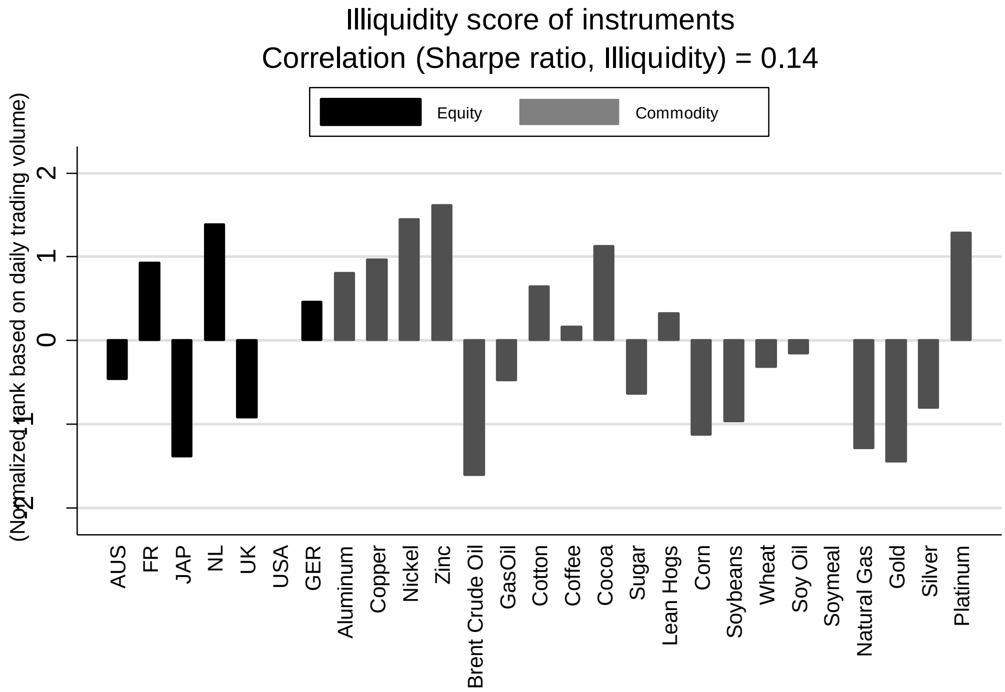


Fig. 3. In the figure are reported the illiquidity scores for each instrument. The illiquidity scores are calculated using normalizing ranks based on daily trading volume from Appendix B.

The correlation result is the opposite of Moskowitz et al. (2012) finding. They found negative weak relationship between illiquidity and Sharpe ratios (-0.16). In Appendix B in table 4 a snapshot of the daily volumes, illiquidity scores and all Sharpe ratios are reported. Therefore, I cannot reject the hypothesis: There is no relationship between the performance of the time series momentum strategy and illiquidity in the cross-section. Since, there is a weak correlation of 0.14 between illiquidity and Sharpe ratios.

Now that the cross-sectional illiquidity is tested against TSMOM, another test for illiquidity is performed. I examined the relationship between the TSMOM returns and some time-varying illiquidity measures. The TSMOM returns are regressed against the TED spread and VIX index separately. The TED spread is also known as the funding liquidity and VIX is an alternative proxy for liquidity as explained in the methodology.

Table 5
In the tables below are reported the coefficients and t-statistics from the regression of the momentum strategy against the Global equity index and illiquidity measures. The first and second regressions are the TSMOM returns against the time-varying liquidity proxies TED spread and VIX index. The third regression is the TSMOM against the MSCI world index and the MSCI world index squared. The strategy is tested for the entire sample period from August 1994 till September 2019.

Panel A: TED spread and Volatility index (VIX)

	MSCI	MSCI (squared)	TED spread	VIX	Intercept	N
Monthly return TSMOM			0.14*		0.02***	299
t-value			(1.76)		(2.09)	
Monthly return TSMOM				0.00***	-0.00	299
t-value				(2.01)	(-0.00)	
Monthly return TSMOM	-0.25	3.63*			0.03***	299
t-value	(-1.37)	(1.71)			(3.68)	

T-statistics are in parenthesis; *** $p<0.01$, ** $p<0.05$, * $p<0.1$

The regression outcomes of Table 5 suggest that the time series momentum strategy has no relationship with TED spread at a 10% significance level. The estimated coefficient of TED spread is 0.14 suggesting that if TED spread increases by 1% the TSMOM returns increases by 0.14% on average. The TSMOM returns are therefore not related to funding liquidity since this magnitude is almost 0. Additionally, the VIX index has no relationship with the TSMOM returns on a 1% significance level. Since, the estimated coefficient of the VIX index is zero. Therefore, the results suggest that there no relationship between time series momentum returns and liquidity. Based on these results, I can reject the hypothesis: There is no relationship between the performance of the time series momentum strategy and time varying liquidity. The conclusions are in line with Moskowitz et al. (2012).

6.3 TSMOM during extreme market

The third regression in Table 5 illustrates the TSMOM return against the MSCI world index and MSCI world index squared. The importance of this regression is the second estimated coefficient MSCI squared. The regression results show that the TSMOM return is insignificant with the MSCI index but is significant with the market index squared on a 10% significance level. This suggest that the TSMOM performs well during market crashes where the returns are in mainly negative. An explanation for this outcome is that the momentum strategy goes short on instruments when markets crashes. In Fig.4 are illustrated the growth of two investment strategies over time for the entire sample period. Here, I compared the TSMOM strategy against the passive long investment strategy. The figure over time shows that the TSMOM returns over performed the passive investment strategy. The TSMOM overtakes the passive investment strategy after the fourth year. In 25 years, the value of the TSMOM portfolio grows to €1.000.000 where the passive investment strategy is €50.000.

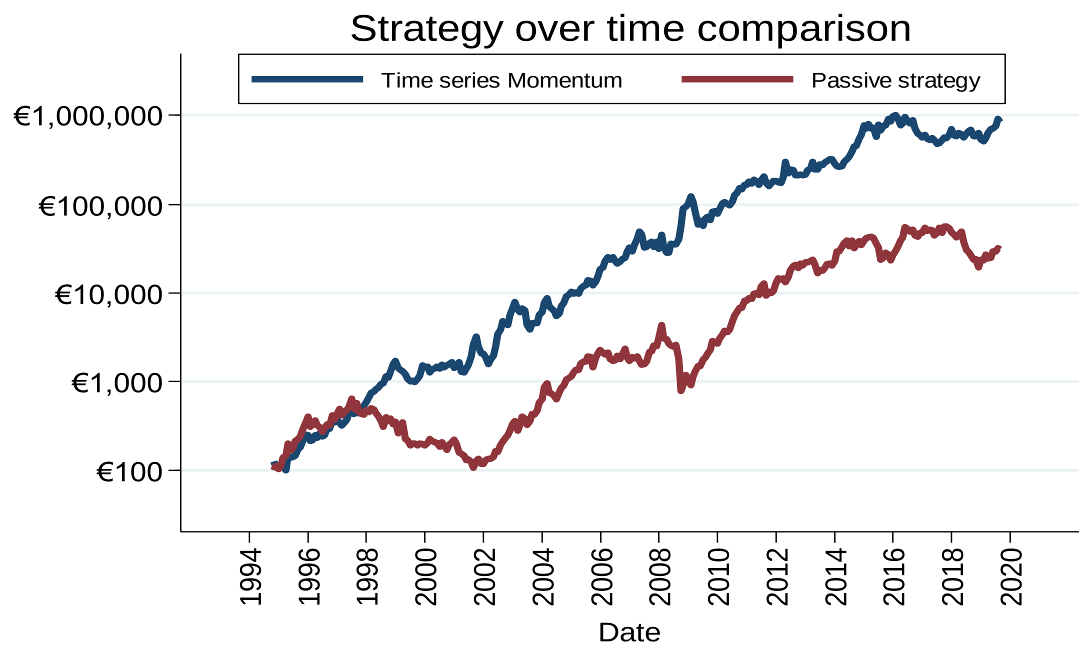


Fig. 4. In the figure are reported the cumulative excess return of the time series momentum strategy and diversified passive long strategy from August 1994 till September 2019.

The results in figure 4 shows another important issue that I discussed earlier. That is the case where the strategy goes short on instruments when the market starts to crash. During the sample period there occurred two well-known markets crashes. The first market crash started from the year 2000 and lasted four years. The figure shows that during this time the value of momentum strategy increased while the passive investment strategy decreased. The second market crash was from 2007 till late 2010. This finding is better explained in Fig.5.

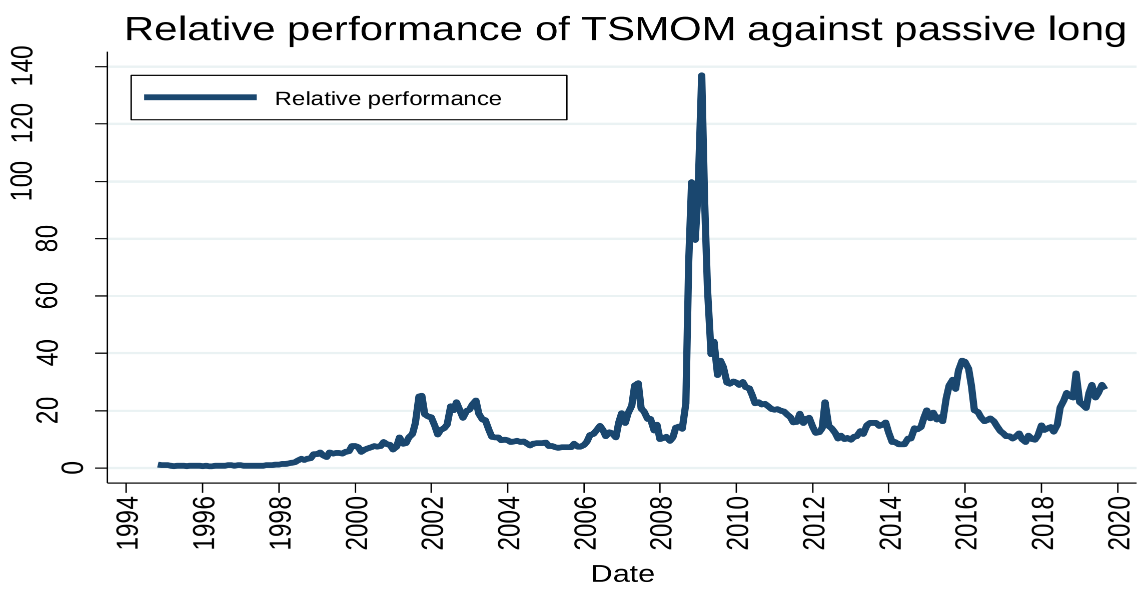


Fig. 5. In the figure are reported the difference between the value growth from €100 TSMOM and passive long strategy from August 1994 till September 2019

Fig.5 shows enormous increase in value for the momentum strategy compared to the passive investment strategy during time of crisis. In particular the global financial crisis influences the strategy very positively compared to the passive long strategy. The figure shows that during that time the value growth to 140 times the size of passive long portfolio. In Appendix C table 6 are illustrated the alphas with their t-statistics of the regressions with TSMOM return against the returns of the passive long investment strategy. The alphas for each instrument are mainly positive and very significant for most equity and 3-years bonds indexes. The alpha for the diversified portfolio is 3% and significant at 1% level. To summarize, the TSMOM returns over performs the passive investment strategy across assets and when looking for instruments separately. Over time the diversified portfolio of TSMOM gains in value extremely well compared to the passive investment strategy. The performance of the strategy is even more noticeable during market crashes since the strategy shorts the instrument. Moskowitz et al. (2012) already showed that the time series momentum strategy outperforms the passive long strategy. This study again shows that the performance during extreme markets is very significant. Based on this information and the significant MSCI global squared return I found earlier, I cannot reject the null hypothesis. The hypothesis stated that there is no positive relationship between the returns of the time series momentum strategy and extreme markets states.

6.4 TSMOM against other factors

Table 7
In the tables below are reported the coefficients and t-statistics from the regression of the momentum strategy against other factors from similar studies. Panel A shows the TSMOM returns against the Fama French factors. Panel B shows the TSMOM returns against the factors from Value and Momentum Everywhere.

Panel A: Fama and French factors						
	MSCI	SMB	HML	UMD	Intercept	N
Monthly return TSMOM	-0.27	-0.21	0.26	4.38	0.04***	299
t-value	(-1.39)	(-0.83)	(0.93)	(0.25)	(5.06)	
Panel B: Value and Momentum Everywhere factors						
	MSCI		VALE	MOME	Intercept	N
Monthly return TSMOM	-0.26		0.56	0.58	0.04***	299
t-value	(-1.41)		(0.89)	(1.12)	(4.63)	

T-statistics are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

In the Table 7 are illustrated the TSMOM returns against factors from two similar studies. The TSMOM returns from a diversified portfolio shows that in both cases it over performs the factor with an alpha of 4% at 1% significant level. The TSMOM returns shows no significance relationship with the factors. Even the cross-sectional momentum factors are not significant which implies that the TSMOM returns are not explained by it. This finding is strange since it is expected that cross sectional momentum should be related to time-series momentum. The finding from Moskowitz et al. (2012) also show that time-series momentum is partly explained by cross-sectional momentum.

6.5 TSMOM Correlation structure

Table 8
In the tables below are reported the correlations of the momentum strategy returns within and across an asset class. Also, the correlation of the passive investment strategy is reported to compare the results. Panel A shows the average pair-wise correlation of instruments within each asset class. Panel B shows the correlation of the returns across asset class for both strategies.

Panel A: Average pair-wise correlation within asset class			
	Equity	Bond	Commodity
Correlation of TSMOM strategy	0.46	0.36	0.07
Correlation of passive long strategy	0.67	0.57	0.15
Panel B: Average correlation across asset classes			
	Equity	Bond	Commodity
	Correlation of TSMOM strategy		
Equity	1.00		
Bond	0.19	1.00	
Commodity	0.22	0.03	1.00
	Correlation of passive long strategy		
Equity	1.00		
Bond	-0.33	1.00	
Commodity	0.27	-0.23	1.00

Table 8 illustrates the correlation of time series momentum strategy within and across an asset class. For comparison I also computed the correlation of passive investment strategy. Panel A which shows the correlation within an asset class, shows that there is positive correlation in the equity class and bond class on average. The correlation is even higher for the passive long strategy. The instruments of the commodity class show little correlation with each other since the correlation here is 0.07. Again, the correlation for the commodity class is slightly higher for the passive investment strategy. Panel B shows the correlation across asset class. The results for TSMOM returns show that the bond and commodity classes are weakly positive correlated with the equity class. However, the bond class is not correlation with the commodities. The passive long strategy shows more diversification since the bond class is weakly negative correlated with the equity class. In Addition, the bond class is also uncorrelated to the commodity class. Only the commodity and equity class show positive relationship with each other. The results show that the on average correlation between instruments within an asset class are lower for the time series momentum strategy. But the asset classes in the momentum strategy are more correlated with each other. Therefore, the portfolio of the time series momentum strategy will be less diversified than the passive investment strategy. Since, the time series momentum strategy is less diversified and subsequently more correlated. I cannot reject the hypothesis which states that: There is less correlation in time series momentum strategy than the passive investment strategy. Thus, risk averse investors should prefer the passive long investment over the time series momentum strategy. However, the results show that the time series momentum has a good potential for risk-seeking investors.

7. Conclusion

In conclusion, the trend analysis shows that there is significant positive trend in the first year across asset classes. However, when testing for separate asset classes the trend seems to be disappear for the commodity class. The best way the time series momentum can profit from this trend is by using a lookback period of 12-months. The 12-months lookback period shows very significant abnormal return against the passive exposure of asset classes and the Fama French factors. The abnormal return of the time series momentum strategy with the 12-months lookback period generates significant positive returns for the equity and bond classes. On the other hand, I find no abnormal return for the commodity class for all lookback periods. When evaluating the instruments separately the results shows that the best performing instruments with the strategy are the 3-years bond indexes. The performances of the strategy on each instrument is predominantly positive. The cross-sectional illiquidity measure suggests that there is a weak positive relationship between illiquidity and the Sharpe ratios of each instrument. Thus, the time series momentum strategy might be driven by the illiquidity sentiment. However, the regression test of time-varying liquidity proxies indicates that there is no relationship between time series momentum returns and liquidity. The time series momentum strategy returns over perform the passive long investment strategy across assets and when looking for instruments separately. Over time the diversified portfolio of time series momentum strategy gains in value extremely well compared to the passive investment strategy. The performance of the strategy is even more noticeable during market crashes. An explanation for this outcome is that the momentum strategy goes short on instruments when markets crashes. When testing the time series momentum returns with similar studies, the strategy returns shows no significance relationship with their factors. Even the cross-sectional momentum factors from Fama-French and Momentum Everywhere are not significant which implies that the time series momentum return are not explained by it. The results show that the asset classes using the time series momentum strategy is more correlated with each other. Therefore, the portfolio of the time series momentum strategy is less diversified than the passive investment strategy.

8. Limitations and future research

In this this study I encountered some methodological limitations. Due to the complex methodology I was not able to test the t-statistic of TSMOM returns against the passive exposure and Fama-French over different holding period for each lookback period. Therefore, I limited the holding period to one-month holding period which is found to be the most significant in the literature: Moskowitz et al. (2012), Blitz and van Vliet (2008) and Fama and French (1996). Another limitation I encountered is that there was no daily volumes available for the bond indexes. Thus, the correlation between the illiquidity of instruments and Sharpe ratios are without the bond instruments. The focus of this study was to highlight TSMOM with the illiquidity and extreme market periods. Due to the limited time of the research I could not provide other important information about the strategy. For instance, true risk measurement like the value at risk and turnover statistic are missing. This information could provide better insight to investors. In particular the turnover statistic is important when comparing the TSMOM against the passive long strategy since the passive strategy has no trading cost during the investment period. By including the trading cost, the value growth of TSMOM would certainly have dropped. Furthermore, in this study I have discussed only one behavioral theory that could explain the time series momentum. However, time series momentum can be linked to several other theories in the literature like the conservatism, representativeness and the disposition effect.

Appendix A

Table 1

Augmented Dickey Fuller unit root test

In this table are reported the results of the Augmented Dickey Fuller unit root test. The Lag length chosen for the ADF equation is three. Column (1) represents the critical value for which the null hypothesis can be rejected at a 1% significance level. Column (3) represents the test statistics resulting from the ADF tests by taking the first differences of the excess return series (i.e., the log returns).

Instruments	**(-1)**	**(-2)**
AUS	-3.456	-8.297***
FR	-3.456	-7.947***
JAP	-3.456	-7.564***
NL	-3.456	-7.597***
UK	-3.456	-7.655***
USA	-3.456	-7.739***
GER	-3.456	-8.094***
AUS3y	-3.456	-8.467***
FR3y	-3.456	-6.298***
JAP3y	-3.456	-6.529***
NL3y	-3.456	-6.136***
UK3y	-3.456	-7.090***
USA3y	-3.456	-8.339***
GER3y	-3.456	-6.449***
AUS10y	-3.456	-8.614***
FR10y	-3.456	-7.218***
JAP10y	-3.456	-10.042***
NL10y	-3.456	-7.254***
UK10y	-3.456	-7.898***
USA10y	-3.456	-8.434***
GER10y	-3.456	-7.527***
Aluminum	-3.456	-7.675***
Copper	-3.456	-7.688***
Nickel	-3.456	-7.904***
Zinc	-3.456	-7.401***
Brent Crude Oil	-3.456	-8.755***
GasOil	-3.456	-8.650***
Cotton	-3.456	-7.543***
Coffee	-3.456	-8.912***
Cocoa	-3.456	-9.265***
Sugar	-3.456	-8.827***
Live Cattle	-3.456	-11.398***
Lean Hogs	-3.456	-10.220***
Corn	-3.456	-8.445***
Soybeans	-3.456	-8.701***
Wheat	-3.456	-9.002***
Soy Oil	-3.456	-7.880***
Soymeal	-3.456	-9.241***
Natural Gas	-3.456	-9.741***
Gold	-3.456	-8.759***
Silver	-3.456	-8.826***
Platinum	-3.456	-8.869***

T-statistics are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

Appendix B

Table 4

Sharpe ratio & Illiquidity factor

Reported are the annualized gross Sharpe ratios of the TSMOM strategy for each instrument, the daily volumes on 15th of November 2019 for each instrument and the illiquidity score. The first column illustrates the gross Sharpe ratios which are calculated by dividing the average annual return of the TSMOM strategy by its annual volatility for the entire sample period from August 1994 till September 2019. The second column is a snapshot of the daily volume for each instrument. In the final column are the Illiquidity score which is calculated by using standard normalization rank based on the daily volumes within each asset class.

Instruments	Sharpe ratio	Daily volume	Illiquidity
AUS	0,26	571.099.892	-0,46
FR	0,63	79.752.283	0,93
JAP	0,39	1.246.370.873	-1,39
NL	0,89	76.188.318	1,39
UK	0,41	745.657.907	-0,93
USA	1,07	484.912.535	0,00
GER	0,52	83.011.618	0,46
AUS3y	2,53		
FR3y	1,74		
JAP3y	3,25		
NL3y	1,78		
UK3y	2,15		
USA3y	0,99		
GER3y	1,05		
AUS10y	1,03		
FR10y	0,91		
JAP10y	0,45		
NL10y	0,78		
UK10y	0,93		
USA10y	0,45		
GER10y	0,88		
Aluminum	0,14	20.089	0,81
Copper	0,55	19.475	0,97
Nickel	0,09	9.859	1,45
Zinc	0,27	8.884	1,61
Brent Crude Oil	0,17	255.681	-1,61
GasOil	0,30	43.405	-0,48
Cotton	0,02	21.825	0,64
Coffee	0,10	25.751	0,16
Cocoa	-0,24	19.055	1,13
Sugar	0,13	54.115	-0,64
Live Cattle	-0,10	21.946	0,48
Lean Hogs	-0,01	23.208	0,32
Corn	-0,01	93.616	-1,13
Soybeans	-0,11	73.352	-0,97
Wheat	-0,22	42.216	-0,32
Soy Oil	-0,02	39.093	-0,16
Soymeal	-0,06	26.385	0,00
Natural Gas	-0,11	168.195	-1,29
Gold	0,46	245.025	-1,45
Silver	0,01	66.100	-0,81
Platinum	0,03	16.106	1,29

Appendix C

Table 6

TSMOM alphas and T-statistic each instrument

Reported are the t-statistic of the alpha for each instrument. I regressed the monthly excess return of the 12-month momentum strategy against the excess return of the passive investment strategy for the entire sample period from August 1994 till September 2019.

Instruments	Alpha	T-statistic	N
Diversified portfolio	0,0332***	4,20	300
AUS	0,002	-0,098	300
FR	0,050***	-2.066	300
JAP	0,037	-1.419	300
NL	0,062***	-2.583	300
UK	0,033	-1.451	300
USA	0,064***	-2.793	300
GER	0,041*	-1.733	300
AUS3y	0,026	-1.568	300
FR3y	0,082***	-4.099	300
JAP3y	0,114***	-5.828	300
NL3y	0,092***	-4.322	300
UK3y	0,043***	-2.319	300
USA3y	0,034	-1.526	300
GER3y	0,067***	-3.100	300
AUS10y	0,011	-0,591	300
FR10y	0,008	-0,519	300
JAP10y	0,014	-0,749	300
NL10y	0,009	-0,472	300
UK10y	0,005	-0,308	300
USA10y	0,001	-0,05	300
GER10y	0,014	-0,837	300
Aluminum	0,013	-0,53	300
Copper	0,051***	-2.054	300
Nickel	0,01	-0,394	300
Zinc	0,027	-1.124	300
Brent Crude Oil	0,018	-0,766	300
GasOil	0,03	-1.262	300
Cotton	0,003	-0,133	300
Coffee	0,007	-0,294	300
Cocoa	-0,035	(-1,425)	300
Sugar	0,018	-0,69	300
Live Cattle	-0,013	(-0,516)	300
Lean Hogs	-0,001	(-0,057)	300
Corn	-0,005	(-0,199)	300
Soybeans	-0,019	(-0,786)	300
Wheat	-0,03	(-1,305)	300
Soy Oil	0,003	(-0,141)	300
Soymeal	-0,01	(-0,383)	300
Natural Gas	-0,015	(-0,637)	300
Gold	0,046*	-1.772	300
Silver	0,001	-0,023	300
Platinum	0,004	-0,142	300

T-statistics are in parenthesis; *** p<0.01, ** p<0.05, * p<0.1

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