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The Momentum Anomaly: Can It Still Outperform the Market?

Master Thesis

by
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Master of Science in Finance

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ABSTRACT

This thesis adds to the already broad literature investigating simple trend-following strategies. We study the ability of a time series momentum strategy to generate abnormal returns following the methodology of Moskowitz et al. (2012). We find evidence of the strategy generating statistically significant returns, even though we further find overwhelming evidence for lower return predictability in the period of 2009-2021. This suggests a diminishing effect of the momentum anomaly. We also find that adding drawdown control as a risk management tool extensively enhances the strategy's performance.

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1 Introduction and Motivation

Ever since Fama (1970) presented his efficient markets hypothesis, there has been an ongoing discussion on the degree of the efficiency in capital markets. Fama's hypothesis suggests that past prices and trading volumes are reflected in current prices, and trading on historical price movements should therefore not generate a significant alpha. The findings of Fama (1970) was later confirmed by Stiglitz (1982), French and Roll (1986), and Lo and MacKinlay (1988). However, Moskowitz et al. (2012) find overwhelming empirical evidence that even a simple trend-following strategy can generate abnormal returns. Trend-following strategies that purely focus on a security's own return, referred to as *Time Series Momentum*, was firstly researched by Daniel et al. (1997), Barberis et al. (1998), and Berk et al. (1999), and was later confirmed by Moskowitz et al. (2012), Asness et al. (2013), Hurst et al. (2014), and Levine and Pedersen (2016). This makes the momentum anomaly is one of the most researched anomalies in the financial markets.

Trend-following strategies were suggested already in the early 1800s by the British economist David Ricardo, as his mantra suggested to "*...cut temporary losses and let the profits run on*" (Pedersen, 2015). This mantra was later repeated by the famous trader Jesse Livermore, who stated that *"... big money was not in the individual fluctuations but ... sizing up the entire market and its trend"* (Pedersen, 2015). Hedge funds utilizing trend-following strategies have existed since at least 1949 and have been proliferated since the 1970s, with the number of funds utilizing trend-following strategies increasing extensively. In other words, strategies such as *Time Series Momentum* are not something new. However, even tough institutional investors exploit it, and numerous renowned researchers further verify it, the return predictability of time series momentum is still widely discussed. The recent literature suggest a diminishing effect of the momentum anomaly, and further a significant tail risk attached to trend-following strategies.

1.1 Research Question

As international researchers disagree about the predictability of time series momentum, we find the theme highly topical. The thesis, therefore, aims to add to the already large body of literature investigating simple trend-following strategies. Firstly, we wish to assess if we obtain the same results as Moskowitz et al. (2012) using an extended sample period, researching if the momentum anomaly still is present in global financial markets. After that, we study if we manage to improve the strategy by adding drawdown control as a risk management tool, reducing its volatility. This leads to the following research question:

Is the momentum anomaly still present in global financial markets, and is it possible to improve a time series momentum strategy by adding drawdown control as a risk management tool?

We use the time series momentum strategy developed by Moskowitz et al. (2012) to evaluate the presence of the momentum anomaly. This means that we do not consider if our results would differ using a cross-sectional momentum strategy. Furthermore, we use instruments from the four largest asset classes, i.e., equities, bonds, commodities and currencies. The instruments we use are among the most liquid and exploited within each asset class, and we therefore presume our data will work as an adequate proxy for global financial markets. Lastly, our research does not emphasize the influence of transaction cost.

1.2 Summary of Findings

We find statistically significant evidence for the presence of the momentum anomaly in our sample period. Following the methodology of Moskowitz et al. (2012), we create a time series momentum strategy, finding that the strategy generates a Sharpe ratio of 0.75, compared to a passive long investment in the same instruments, generating a Sharpe ratio of 0.73. We further find that when adjusting for relevant risk factors, the strategy generates a statistically significant monthly alpha of 0.44%, supplying evidence against the efficient market hypothesis of Fama (1970).

However, we also find overwhelming evidence of lower to zero return predictability during the last decade. When controlling three independent subperiods, we find that the strategy generates a negative alpha in the period of January 2009 to December 2021. Even though the alpha is insignificant, the strategy generated a positive and statistically significant alpha in the two other subperiods. This insignificance suggests that the effect of the momentum anomaly is diminishing, and that the markets are more efficient than first assumed, supporting the efficiently inefficient hypothesis of Pedersen (2015). The lower return predictability can be explained by the results of McClean and Pontiff (2016), as they find low return predictability in heavily researched anomalies. In addition, research by Cotter and McGeever (2018) suggests a diminishing effect of the momentum anomaly in the U.K.

Finally, we find that adding drawdown control as a risk management tool enhances the strategy's performance, both in terms of Sharpe ratio, and in terms of risk-adjusted return. The Sharpe ratio of the strategy with drawdown control is 1.07, compared to 0.75 without. Adding drawdown control also increases the abnormal return of the strategy, improving the monthly alpha by seven basis points.

2 Literature review

Relevant literature has been reviewed thoroughly. First, we explore the broad literature discussing trend-following strategies and drawdown control as a risk management tool, setting the empirical foundation for our thesis. Second, we look into theory discussing the efficient market hypothesis, which lays the theoretical foundation for whether past prices and trading volumes are reflected in current prices. Thereafter, we focus on theory explaining the economic rationale behind trend-following strategies, before we review theory exploring the economic interpretation of drawdown control. We regard these topics as essential to review as they give both an empirical and a theoretical framework for our thesis.

2.1 Time Series Momentum

Moskowitz et al. (2012) conclude that the past 12-month return could positively predict the return for the next one to 12 months. They also conclude that a time series momentum strategy could earn a significant average- and risk-adjusted return. This finding is further examined by Asness et al. (2013), Hurst et al. (2014), and Levine and Pedersen (2016), who investigate different forms of times series momentum on new asset classes and sample periods, finding the same results as Moskowitz et al. (2012).

However, Kim et al. (2016) explain that the time series momentum strategy is driven by volatility scaling and that its performance without this scaling is not significantly better than an ordinary buy-and-hold strategy. In a parallel study, Goyal and Jegadeesh (2018) show that if you adjust the leverage ratio appropriately, a traditional cross-sectional momentum strategy will generate higher returns than time series momentum. Due to these findings, the return predictability of time series momentum is disputed.

Huang et al. (2020) find little statistical and economic evidence of time series momentum when using the same data as Moskowitz et al. (2012). They conclude that the presence of the momentum anomaly across the global asset classes is questionable. By adopting the methodology of Moskowitz et al. (2012), running a pooled regression, they find strong evidence against no predictability. Huang et al. (2020) argue that the pooled regression used by Moskowitz et al. (2012) is likely to over-reject the null hypothesis due to upwards bias (Hjalmarsson, 2010), persistence in the past 12-month returns (Li and Yu, 2012), and volatility scaling (Kim et al., 2016). When separating the volatility effect, Huang et al. (2020) find that the performance of the time series momentum strategy does not necessarily originate from predictability. They further find that the trend-following strategy has little predictive power, based on the predictive slope developed by Lewellen (2011). Huang et al. (2020) end their argumentation by stating that they do not claim that there is no predictability in any asset class, but that the predictability is not as simple as a constant 12-month return rule. Risk premium in the stock market can be predicted by a range of macroeconomic variables and investor sentiments, as shown by Jiang et al. (2019).

Another criticism of trend-following strategies is the transaction cost. Lesmond et al. (2003) state that the assets creating significant momentum returns are also the assets with highest trading cost. They conclude that the abnormal returns associated with following a momentum strategy create a phantasm of returns, as they do not exist. Furthermore, Korajczyk and Sadka (2004) conclude that trading on the momentum anomaly is only profitable on a tiny scale. However, Novy-Marx and Velikov (2016) argue that these papers study the obsolete momentum strategies, and not the strategies designed to minimize transaction cost. They point to the findings of Frazzini et al. (2012), who conclude that the momentum anomaly is robust and implementable, and that the potential scale of the strategy is substantially larger than what previous studies have suggested. These findings are further supported by the results of Hurst et al. (2014), stating that time series momentum, following the methodology of Moskowitz et al. (2012), has generated a consistent positive return over the last century, net of transaction costs and management fee.

An essential addition to the literature discussing the predictability of time series momentum is whether the momentum anomaly is diminishing. As discussed by McClean and Pontiff (2016) in *Does academic research destroy stock return predictability?*, investors learn about mispricing from academic publications. In their research, the authors find significantly lower predictability in the returns of publication-informed trading. McClean and Pontiff (2016) especially emphasize the role of hedge funds in exploiting market anomalies, which ultimately increases the efficiency grade of the market. Moreover, Boehmer and Kelley (2009) find that stocks with a higher grade of institutional ownership exhibit lower predictability in returns. Finally, the phenomenon that the momentum effect is starting to evaporate is researched by Cotter and McGeever (2018), finding that in the U.K., the return of trend-following strategies has been decreasing after 2007.

2.2 Drawdown Control

Grossman and Zhou (1993) define drawdown control as a reactive mechanism that seeks to limit losses as they evolve. Drawdowns are costly, as they, in addition to direct losses, can lead to increasing margin requirements from prime brokers (Pedersen, 2015). We use drawdown control to minimize the risk that the drawdowns of the strategy exceeds a prespecified maximum acceptable drawdown (MADD). If the current drawdown in time t is given by DD_t, then Pedersen (2015) suggests the following drawdown control policy:

$$VaR_t \leq MADD - DD_t \tag{1}$$

The right-hand side of the equation illustrates the largest acceptable loss given the amount already lost. In contrast, the left-hand side shows the most that can be lost given the current positions and market risk, at a certain confidence level (Pedersen, 2015). Drawdowns are calculated from the current *high water mark*, i.e., the highest cumulative return achieved by the strategy in the period. When the strategy does not experience a drawdown, the high water mark increases until a subsequent drawdown occurs.

If Equation (1) is violated, one should reduce risk by unwinding positions until VaR reaches a satisfying level. Gray and Vogel (2013) argue that drawdown can be used as a simple method to capture the tail risk, which is often unnoticed by linear factor models like the Fama-French-Carhart Four-Factor Model. They study the tail risk in market anomalies, finding an extreme tail risk in a long/short strategy like time series momentum. Furthermore, they find the usefulness of using drawdown to manage tail risk as significant.

Drawdown challenges a manager's financial and psychological tolerance. According to Chekhlov et al. (2000), a drawdown of 50% is unlikely to be tolerated in any average account. Furthermore, Chekhlov et al. (2005) argue that an account may be closed even if the drawdown breaches 20%. Finally, Gray and Vogel (2013) argue that the drawdown of a long/short momentum portfolio will, in most cases, be so extreme that an investor would most likely suffer direct margin calls via direct broker intervention or indirect margin calls via forced liquidations. As shown by Zhou and Zhu (2009), the probability of a 50% drawdown to happen over a century, even if the stock markets are modeled as a random walk, is 90%. This emphasizes the importance of having control over the drawdowns of a strategy.

3 Theory

3.1 Efficient Capital Markets

In *Efficient Capital Markets: A Review of theory and Empirical work*, Fama (1970) presented his efficient market hypothesis. Fama argues that an efficient market is where prices reflect all relevant information. He states that it is difficult, or even impossible, to predict prices in the short run, as the market incorporates stock news into prices. In efficient markets, the market price always equals the fundamental value, and if any news gets out, the market will immediately react to reflect the new information. Therefore, there is no point in active investing, and investors should buy the market instead of trying to beat it. Fama (1970) further introduced three forms of market efficiency - *Weak Form*, *Semi-Strong Form*, and *Strong Form*. The weak form suggests that prices reflect information about historical prices, making a trading strategy based on historical prices, like time series momentum, of no value. The semi-strong form states that the market reflects all publicly available information, making trading based on underlying firm fundamentals useless. The strong form of market efficiency indicates that prices reflect all public and private information. Fama (1970) observe extensive evidence for his efficient markets model, finding support for both the weak- and the semi-strong form. This research was later tested and confirmed by Stiglitz (1982).

Shiller (2003) provides a new view in this discussion in his article *From efficient markets theory to behavioral finance*. Shiller show that stock prices move away from their fundamental value more than standard theory can explain, arguing that markets do not reflect all information. Furthermore, Shiller argues that the prediction of price development is possible in the medium to long run. Hence, he argues that markets are less efficient than first assumed. This argument opposes the efficient market hypothesis of Fama (1970). If Fama is correct, then time series momentum will not be able to generate abnormal returns, as all historical information is reflected in the stock price. However, as described previously, there is overwhelming evidence that simple trend-following strategies can generate abnormal returns. Hence, markets cannot be fully efficient. At the same time, Pedersen (2015) argues that markets cannot be as inefficient as Shiller describes, as then everyone would beat the market.

In his book *Efficiently Inefficient: How smart money invests & market prices are determined*, Pedersen (2015) gives new insight to this discussion. He argues that markets are just so *inefficient* that money managers can be compensated for their costs and risk through superior performance. On the other hand, he also argues that the markets are just *efficient* enough that the returns investors generate on active investing after all costs do not encourage the entry of new managers or additional capital. Hence, Pedersen argues for something between Fama and Shiller. The markets are *efficiently inefficient* (Pedersen, 2015). In other words, generating positive abnormal returns on a simple trend-following strategy *could* be possible, as the market does not fully incorporate all information. According to Pedersen (2015), managers in an inefficient market are compensated for providing liquidity to the market, i.e., helping investors transact. Money managers are compensated for taking the other side of these trades due to the liquidity risk they expose upon themselves. Financial market frictions influence the real economy and also the efficiency of markets. These frictions' effects are also supported by the findings of Acharya and Pedersen (2003) and Garleanu and Pedersen (2011).

3.2 Economic Interpretation of Time Series Momentum

Pedersen (2015) describes a trend-following strategy's economic rationale by illustrating a trend's "life cycle." At first, an initial underreaction to a shift in the fundamental value allows the strategy to invest before the market incorporates the information. As a trend-following strategy buys the assets due to the initial upward price move, it capitalizes as the price will continue to increase due to the initial underreaction. Several behavioral tendencies and market frictions are leading to this phenomenon. Duffie (2010) argues that market frictions delay the response, leading to a drop and rebound in prices. Mitchell and Pulvino (2012) point out that people tend to sell winners too early and ride losers too long. When there are fewer sellers in the market, this keeps prices from adjusting as fast as they should. Furthermore, investors tend to be biased towards historical data, insufficiently adjusting their views to new information.

After the initial underreaction, a trend starts. The cycle continues when the asset experiences a delayed overreaction. Research finds several phenomena that extend the trend beyond the asset's fundamental value. Daniel et al. (1997) show that people tend to look for information that confirms their beliefs, looking at recent price moves as representative of the future. This leads investors to move capital into assets that are increasing, and out of assets that are decreasing. Vayanos and Woolley (2013) argue that when prices have moved, some investors follow the stream, so-called "herding." Herding has been documented in the forcasts of equity analysts, earnings forecasts, and institutional investment decisions. Vayanos and Woolley (2013) also discuss the fund flows of institutional managers. As managers underperform, investors will withdraw their money, forcing the manager to reduce his position, hence selling losers. On the other hand, managers overperforming will experience an inflow of cash, adding buying pressure to winning stocks. All these phenomena are strengthening the initial underreaction and the overreaction, continuing the trend. However, in the end, no trend lasts forever. Pedersen (2015) argues that at some point, prices extend far beyond fundamental value. As investors recognize this, prices will revert to the fundamental value, and the trend will die.

According to theory, time series momentum generates the most considerable returns during extreme markets. According to Fung and Hsieh (2001), this is because the strategy goes long when the market has a significant upswing, and then short when the market crashes. This theory is further supported by the findings of Moskowitz et al. (2012) and Pedersen (2015), stating that a simple trend-following strategy historically has performed best in significant bull- or bear markets, while generating lower return when the market is flat. The logic behind this is that deep bear markets often occur when markets go from "bad" to "worse," causing traders to panic and prices to collapse. Collapsing prices will make the short positions of the strategy generate large returns, explaining why the strategy is profitable during such events. However, a look-back period that is too long can lead to substantial losses. In the case of sharp trend reversals, the strategy will not manage to alter its positions, inducing losses.

3.3 Economic Interpretation of Drawdowns

Using drawdown control could be compared to an investor trying to identify trends that have pushed the price far beyond the asset's fundamental value, also called overextended trends (Pedersen, 2015). With drawdown control, a strategy can pinpoint such overextended trends, limiting losses from sharp trend reversals. As Pedersen (2015) further describes, drawdown control also gives the strategy the ability to recognize short-term counter-trends, improving the strategy's performance in range-bound markets. Combined, the limitation of losses and the identification of short-term counter-trends ultimately increase the returns of a strategy (Pedersen, 2015).

4 Data

To replicate the results of Moskowitz et al. (2012) we try to retrieve the same data used in their research. The data include futures prices for 24 commodities, 12 cross-currency pairs, nine developed equity indices, and 13 developed government bond futures. As all of the instruments are among the most liquid futures in the market, we believe our results are not biased by illiquidity nor stale prices.

Since BI Norwegian Business School does not have the same data access as Moskowitz et al. (2012), we need to do adjustments for some asset classes. These adjustments are explained in Appendix A. We retrieve our data mainly from Bloomberg and Datastream. As each asset class is composed of instruments from different countries, we experience problems as stock exchanges worldwide do not have the same opening days throughout the year. Therefore, we simplify by assuming that prices are constant when the exchanges are closed. To do this, we align all daily data with the correct date from 01.01.1985 - 31.12.2021. In addition, for the securities that are missing data on a specific date, we assume the price is the same as the day before. By making these adjustments, we have a data set with prices for all futures and their corresponding proxies. Table 1 provides sample statistics on each instrument; their start date, their annualized mean, and their annualized volatility.

	Data start date Our data	Annualized mean Our data	Annualized volatility Our data	Data start date Moskowitz et al.	Annualized mean Moskowitz et al.	Annualized volatility Moskowitz et al.
Commodity futures						
ALUMINIUM	Jun-86	3.91%	20.69%	Jan-79	0.97%	23.50%
BRENTOIL	Jun-88	11.46%	36.32%	Apr-89	13.87%	32.51%
CATTLE	Jan-85	3.58%	17.94%	Jan-65	4.52%	17.14%
COCOA	Jan-85	5.1%	29.93%	Jan-65	5.61%	32.38%
COFFEE	Jan-85	0.%	36.89%	Mar-74	5.72%	38.62%
COPPER	Apr-86	8.26%	24.33%	Jan-77	8.9%	27.39%
CORN	Jan-85	5.76%	26.83%	Jan-65	-3.19%	24.37%
COTTON	Jan-85	5.87%	28.83%	Aug-67	1.41%	24.35%
CRUDE	Jan-85	1.05%	67.91%	Mar-83	11.61%	34.72%
GASOIL	Jul-89	10.58%	34.11%	Oct-84	11.95%	33.18%
GOLD	Jan-85	6.16%	16.17%	Dec-69	5.36%	21.37%
HEATOIL	Jul-86	11.98%	36.41%	Dec-78	9.79%	33.78%
HOGS	Apr-87	8.24%	36.08%	Feb-66	3.39%	26.01%
NATGAS	Apr-90	17.51%	54.86%	Apr-90	-9.74%	53.30%
NICKEL	May-87	12.24%	35.71%	Jan-93	12.69%	35.76%
PLATINUM	Jan-85	3.97%	24.02%	Jan-92	13.15%	20.95%
SILVER	Jan-85	7.81%	28.95%	Jan-65	3.17%	31.11%
SOYBEANS	Jan-85	6.16%	16.17%	Jan-65	5.57%	27.26%
SOYMEAL	Jan-85	6.69%	27.2%	Sep-83	6.14%	24.59 %
SOYOIL	Jan-85	4.82%	23.23%	Oct-90	1.07%	25.39%
SUGAR	Jan-85	10.84%	36.77%	Jan-65	4.44%	42.87%
UNLEADED	Apr-87	13.3%	40.6%	Dec-84	15.92%	37.36%
WHEAT	Jan-85	6.61%	29.7%	Jan-65	-1.84%	25.11%
ZINC	Jan-89	5.58%	25.49%	Jan-91	1.98%	24.76%
Equity index futures						
ASX SPI 200 (AUS)	Jan-85	7.93%	16.72%	Jan-77	7.25%	18.33%
DAX (GER)	Jan-85	10.49%	22.54%	Jan-75	6.33%	20.41%
IBEX 35 (ESP)	Jan-85	8.3%	22.62%	Jan-80	9.37%	21.84%
CAC 40 10 (FR)	Jan-85	8.71%	21.82%	Jan-75	6.73%	20.87%
FTSE/MIB (IT)	Jan-85	7.41%	18.45%	Jun-78	6.13 %	24.59%
TOPIX (JP)	Jan-85	4.46%	22.1%	Jul-76	2.29%	18.66%
AEX (NL)	Jan-85	8.12%	20.81%	Jan-75	7.72%	19.18%
FTSE 100 (U.K.)	Jan-85	6.53%	18.45%	Jan-75	6.97%	17.77 %
S&P 500 (U.S.)	Jan-85	10.92%	19.26%	Jan-65	3.47%	15.45%
Bond futures						
3-year AUS	May-88	0.35%	1.27%	Jan-92	1.34%	2.57%
10-year AUS	Jan-85	0.36%	1.31%	Dec-85	3.83%	8.53%
2-year EURO	Jun-97	0.72%	1.17%	Mar-97	1.02%	1.53%
5-year EURO	Okt-91	1.32%	3.44%	Jan-93	2.56 %	3.22 %
10-year EURO	Nov-91	2.49%	5.65%	Dec-79	2.40%	5.74%
30-year EURO	Okt-98	3.25%	12.77%	Dec-98	4.71 %	11.70%
10-year CAN	Jan-95	3.87%	5.72%	Dec-84	4.04%	7.36%
10-year JP	Dec-86	1.18%	4.62%	Dec-81	3.66%	5.40%
10-year U.K.	Jan-85	2.85%	7.12%	Dec-79	3.00%	9.12%
2-year U.S.	Jun-90	1.29%	1.55%	Apr-96	1.65%	1.86%
5-year U.S.	May-88	2.6%	3.87%	Jan-90	3.17 %	4.25 %
10-year U.S.	Jan-85	4.17%	6.26%	Dec-79	3.80%	9.30%
30-year U.S.	Jan-85	8.89%	10.13%	Jan-90	9.50%	18.56%
Currency forwards						
AUD/USD	Jan-85	0.35%	11.91%	Mar-72	1.85 %	10.86%
EUR/USD	Jan-85	1.79%	10.69%	Sep-71	1.57%	11.21%
CAD/USD	Jan-85	0.39%	7.49%	Mar-72	0.60%	6.29%
JPY/USD	Jan-85	2.68%	10.81%	Sep-71	1.35%	11.66%
NOK/USD	Jan-85	0.74%	11.36%	Feb-78	1.37%	10.56%
NZD/USD	Jan-85	1.73%	12.17%	Feb-78	2.31 %	12.01%
SEK/USD	Jan-85	0.61%	10.96%	Feb-78	-0.05%	11.06%
CHF/USD	Jan-85	3.48%	11.62%	Sep-71	1.34%	12.33%
GBP/USD	Jan-85	0.91%	10.02%	Sep-71	1.39%	10.32%

Table 1: Summary statistics of futures contracts

Tab.1. The table shows summary statistics of each instrument for our data and the data of Moskowitz et al. (2012). We report the annualized mean and volatility as well as the start date of the data.

4.1 Data Quality

Due to access limitations, we are not able to retrieve the same data as Moskowitz et al. (2012). We do however assess that since we use Bloomberg and Datastream as our data sources, the quality of the data we retrieve is adequate. Nonetheless, we see some differences when comparing our results in Table 1. For bonds, the annualized mean and the annualized volatility is, on average, lower in our data than in the findings of Moskowitz et al. (2012). There could be several reasons for this difference. However, we deem the source and length of the data as the most probable causes, and therefore find the quality sufficient for replication.

For currencies, the data is retrieved from a different source than Moskowitz et al. (2012). However, when comparing our results to Moskowitz et al. (2012) the difference is not momentous, especially considering the volatility. Looking at the average return, we see that Moskowitz et al. (2012) report a slightly negative return for SEK/USD, while we have a positive return. This difference can be explained if we look at the development of the exchange rate over the last ten years, where the dollar has appreciated relative to the Swedish Krona.

In regards to commodities, we see that overall sample statistics are quite similar for our data and the data used by Moskowitz et al. (2012). This similarity is not surprising, as both retrieve their data from Bloomberg, and the sample length is virtually the same. We do, however, notice that Moskowitz et al. (2012) report a negative annualized mean for Corn, Natural Gas, and Wheat. For Corn and Wheat, the authors' data starts in 1965, including a large drop in the price that we do not have in our data. The two commodities also experience a large price increase after 2009, explaining why our annualized return is positive. For Natural Gas, we believe the negative return shown in Moskowitz et al. (2012) is explained by the large price decrease in 2008, following the financial crisis. The return do, however, double after 2009, explaining our positive returns. The extensive development of commodity return after 2009 is illustrated in Figure 11.

On average, our equity index futures have a higher return than the findings of Moskowitz et al. (2012). This difference is logical, as their data ends after the financial crisis, while we see a massive increase in return after 2009, illustrated in Figure 11. The stock market has recovered after the financial crisis, and we, therefore, see higher returns in our data. The difference is exceptionally high in the returns of the S&P 500, but as we show in Figure 11, the index has more than tripled since 2009.

5 Methodology

Using the historical prices for all instruments we create return series'. As futures do not require a upfront investment, our returns are already excess, giving us the daily excess return. We compound the daily excess returns to a cumulative return index for all secuirities, making it possible to compute returns at any horizon within the range or sample period. Table 1 presents summary statistics for all instruments.

5.1 Ex Ante Volatility Estimate

As shown in Table 1, the volatility varies dramatically across all assets. Therefore, as Moskowitz et al. (2012), we scale the returns by their volatility to make meaningful comparisons across instruments. In detail, we estimate each asset's ex ante volatility, σ_t^2, at each point in time using a simple univariate GARCH model; the exponentially weighted lagged squared daily returns. The advantage of this model is that we avoid volatility clustering. Moreover, the model considers potential heteroskedasticity in the data, assuming autocorrelation in the variance error term. The formula is calculated as follows:

$$\sigma_t^2 = 261 * \Sigma_{i=0}^{\infty} * (1-\delta) * \delta^i * (r_{t-1-i} - \bar{r}_{t-1}) \qquad (2)$$

The variance is returned in annual terms by the scalar 261, i.e., assuming 261 trading days a year. The weights in the model, $(1-\delta)\delta^i$, add up to 1, and $\bar{r}_{t-1}$ is the exponentially weighted average return. Furthermore, the parameter δ is chosen as $\Sigma_{i=0}^{\infty} * (1-\delta) * \delta^i * i = \delta/(1-\delta) \; = 60$ days, stating that the center of mass of the weights equals 60 days.

The model is not altered for any instrument. As we are using volatility estimates at time t - 1, we are limiting the probability of look-ahead bias contaminating the results, making it comparable to Moskowitz et al. (2012).

5.2 Time Series Momentum Trading Strategy

The in-depth analysis of time series momentum (TSMOM) in Moskowitz et al. (2012) focuses on the properties of a 12-month TSMOM strategy with a one-month holding period. We therefore do the same. We consider whether each asset's excess return over the past 12 months is positive or negative. If the return is positive, we go long the instrument, and if negative, we go short. In both cases, we hold the instrument for one month. For each instrument, we scale it with $40\% * \frac{1}{\sigma^2_{t-1}}$, each month. 40% represents the risk of an average individual stock, and by doing this, we size each position in the strategy to have constant ex ante volatility (Moskowitz et al., 2012). This scaling is helpful as aggregating strategies across instruments with the same volatility levels are easier. Furthermore, having a time series with relatively stable volatility prevents the strategy from being dominated by a few volatile periods (Moskowitz et al., 2012).

To derive the time series of monthly returns, we follow the methodology used by Jegadeesh and Titman (1993). The return at time t represents the average return across the instruments at that time, i.e., the return of the portfolio that was constructed last month. We compute the time-t return for each asset based on the positive or negative past return from time t-k-h to t-h, where $k = 12$ and $h = 1$. The result is a time series of monthly returns from the portfolio we hold for one month. Taking the average return across all instruments within an asset class then gives us the return of our strategy, defined as $r^{TSMOM}_{t,t+1}$. Specifically, the TSMOM return for any instrument s at time t is given by:

$$r^{TSMOM,s}_{t,t+1} = sign(r^s_{t-12,t}) * 40\% * \frac{1}{\sigma^s_t} * r^s_{t,t+1} \tag{3}$$

Using this equation, we compute the return for each instrument in each available month from January 1985 to December 2021. The overall return of the strategy, consisting of an equally-weighted portfolio of the different securities, can be written as:

$$r_{t,t+1}^{TSMOM} = \frac{1}{S_t} * \sum_{s=1}^{S_t} * sign(r_{t-12,t}^{s}) * 40\% * \frac{1}{\sigma_t^s} * r_{t,t+1}^{s} \quad (4)$$

where S_t represents the number of available securities at time t.

5.3 Asset Pricing Benchmark

Jensen (1968) uses the Capital Asset Pricing Model (CAPM) to evaluate how mutual funds perform. The research of Jensen (1968) states that an alpha value different from zero either imply that the fund either creates or destroys. Fama and French (1993) later expand the model of Jensen (1968), stating that market movements cannot solely explain stock returns. They extend the model by adding two additional factors, *Small-Minus-Big* (SMB) and *High-Minus-Low* (HML). SMB is a size strategy, going long small cap stocks and short-selling large cap stocks. HML is a value strategy, buying value stocks and shorting growth stocks. This model is named *The-Fama-French three-factor model* (FF3 model). Carhart (1997) further supplements the FF3 model by adding the cross-sectional momentum factor *UMD* of Jegadeesh and Titman (1993). UMD measures exposure towards time-varying risk, as the cross-sectional momentum strategy buys winning stocks and shorts losing stocks in the cross-section. This model of Carhart (1997) is referred to as *The Fama-French-Carhart Four-Factor Model.*

To evaluate the risk-adjusted performance of the strategy we follow the methodology of Moskowitz et al. (2012), using the Fama-French-Carhart Four-Factor Model. We use MSCI World Index as a proxy for the stock market factor, *MKT*. The MSCI World Index is a stock market index covering over 1500 companies in 24 countries. The index is weighted by market capitalization and is commonly used as a benchmark for the global market, representing a broad cross-section of world stocks. Furthermore, we retrieve the *SMB*- and *HML*-factors from Kenneth French's homepage, and the *UMD*-factor from Bloomberg.

In addition, we also control for exposure to the bond market, proxied by Barclays Aggregate Bond Index, and the commodity market, proxied by the S&P GSCI Index. This is because the Carhart Four-Factor Model mainly measures exposure to the stock market. We believe adding the bond and commodity markets when risk-adjusting the performance of the time series momentum strategy will give more robust results.

Barclays Aggregate Bond Index is a market capitalization-weighted index representing the U.S. bond market. We use this bond index as a proxy for the bond market for several reasons. Firstly, the U.S. bond market alone constitutes nearly 40% of the total bond market in the world. Furthermore, USD is the world currency for financial markets, and USD fluctuations will therefore affect both the U.S. bond market and the world bond market. Another alternative could have been the FTSE World Government Index. However, our assessment is that this index puts too much emphasis on government bonds that are irrelevant to our strategy.

The S&P GSCI Index is an index covering the futures market of commodities. The index consists of the exact same commodities as in our strategy. The index uses a production weighting, giving weight to each commodity according its average production quantity. This is advantageous as it gives the index the trait of measuring investment performance and additionally work as an economic indicator.

5.4 Violations of Ordinary Least Square Assumptions

In the thesis, we use the Ordinary Least Square model (OLS) to assess the risk-adjusted performance of the strategy. For the OLS to be the best linear unbiased estimator (BLUE), several assumptions need to hold. Even though some researchers run diagnostics to test for violations of these assumptions, we have chosen not to do this. Instead, we follow the methodology of Fama and French (1993) and Carhart (1997) when assessing risk-adjusted returns, i.e., not adjusting for any violations. This methodology is also adopted by Moskowitz et al. (2012). A violation of the assumptions might impact the significance of our observations, leading to misleading results. However, we find it sensible to not adjust as we compare our results with Moskowitz et al. (2012).

Assessing each of the assumptions, the plotting of quarterly returns in Figure 5 more or less rejects the hypothesis of linearity in the residuals. Violating second assumption of normality in the data, could lead to a biased alpha. However, because of our large sample size, we believe the Central Limit Theorem will make the data approximately normalized. Therefore, we assess that the alphas in our regressions are statistically robust. Regarding heteroscedasticity in the data, this is common in time series regressions, and could lead to invalid observations. Therefore, violating this assumption might affect our results. Moreover, we expect that there will be autocorrelation in the data. A simple trend-following strategy takes advantage of autocorrelation, and adjusting for it would offset our strategy. As for the last assumption of no multicollinearity, this does not have any noteworthy influence on our results.

6 Results and Analysis

In this section we will present the results of our analysis and further discuss the impact of our findings.

6.1 TSMOM Predictability of Future Returns

By regressing the excess return r_t^s for each instrument s in month t on its return lagged h months, where we scale the returns by their ex ante volatility's σ_{t-1}^s, we examine the time series predictability of future returns like Moskowitz et al. (2012). Hence, we have the following regression:

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h \frac{r_t^s}{\sigma_{t-h-1}^s} + \varepsilon_t^s \tag{5}$$

As shown in Table 1, the volatility of each asset class varies vastly. Moskowitz et al. (2012) therefore scale all returns by their volatility to have them in relevant measurements. Qualitatively, the regression results will be similar to running an OLS regression without adjusting for each security's volatility. The method can therefore be compared to the Generalized Least Square (GLS) method. As the time series momentum relies on past returns, there will be a certain degree of correlation between the residuals in the regression. Therefore, when measuring the predictability of the strategy, the GLS is a more fitting model.

Using all futures contracts in our data, we run a pooled panel regression and compute t-Stats that account for group-wise clustering by time (monthly level). In the regression, we used lags of h = 1, 2, ..., 60 months. This method is the same procedure as Moskowitz et al. (2012), and allows us to compare our results.

To verify that we successfully manage to replicate the results of Moskowitz et al. (2012), we test the predictability of the time series momentum strategy in regression specification (5) using the same sample length as they have in their study. A comparison of the findings is visualized in Figure 1. The panel to the right shows the findings of Moskowitz et al. (2012), while the panel to the left illustrates our results. As the figure shows, we observe numerous similarities when using the same sample length. Firstly, we see a pattern of positive and significant t-Stats when looking at the first 12 lags. This similarity underpins that we have data and a strategy that captures the same trends as Moskowitz et al. (2012). Secondly, we have a significant reversal in month 13, and even more significant than Moskowitz et al. (2012). These points indicate a continuation of returns for the first 12 months, continued by a reversal of the returns, just like the strategy we are replicating. However, looking at the t-Stats for the regressions with more extended look-back periods, our results differ as we have more positive t-Stats. This indicates that although we manage to capture the same trends, the data have some differences. Secondly, this implies that our strategy will not be a perfect replication. Nevertheless, we asses our results to demonstrate a successful replication of the strategy.

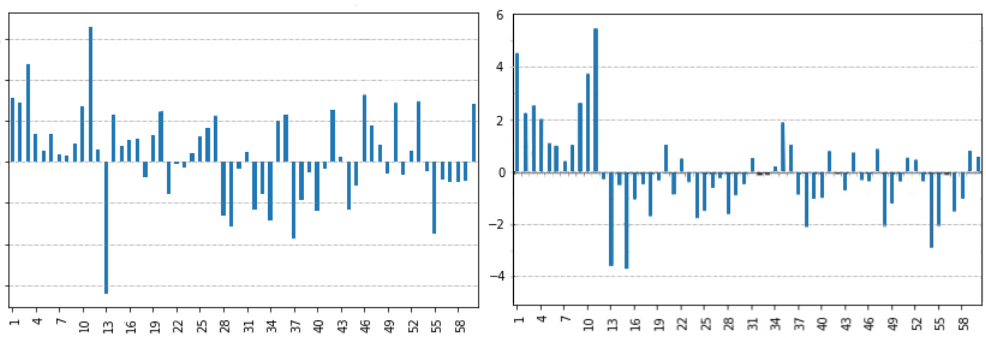

Figure 1: Comparison with Moskowitz et al. (2012) of t-Stats for all asset classes

Fig.1. The figure compares our findings with the findings of Moskowitz et al. (2012). In the panel to the right we find the time series predictability across all assets of Moskowitz et al. (2012), and to the left is our results. To calculate the predictability, we regress the monthly return of each instrument on its own lagged return over different time lengths, $\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h \frac{r_t^s}{\sigma_{t-h-1}^s} + \varepsilon_t^s$. In this regression, we use the size of the lagged return as a predictor, scaling returns by their ex ante volatility to make meaningful comparisons across assets. Sample period is January 1985 to December 2009.

Figure 2 plots the t-Stats from the pooled regression by month lag h for all asset classes for the full sample, i.e., from January 1985 to December 2021. We observe the same trends as in Figure 1. However, we see than when extending the sample period, the return predictability of the strategy decreases, with only two out of 13 t-Stats being significant on a 5% level. The lower significance suggest a downgrade in return predictability after 2009, pointing towards low statistical evidence of the momentum anomaly.

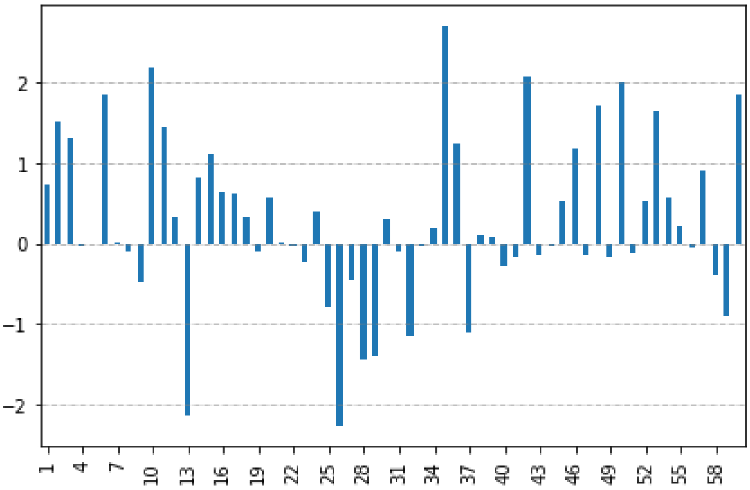

Figure 2: T-Stats for all asset classes with lagged return as predictor

Fig.2. The panel shows the time series predictability across all assets for the full sample period, i.e., from January 1985 to December 2021. We regress the monthly return of each instrument on its own lagged return over different time lengths, $\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h \frac{r_t^s}{\sigma_{t-h-1}^s} + \varepsilon_t^s$. In this regression, we use the size of the lagged return as a predictor, scaling the returns by their ex ante volatility to make reasonable comparisons across asset classes. Sample period is January 1985 to December 2009.

We further look at the time series predictability only focusing on the sign of past excess returns. We use the following regression:

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

where $sign(r_{t-h}^s)$ represents whether the past excess returns are negative or positive, taking the value of 1 if positive and -1 if negative. To make reasonable comparisons across asset classes, we scale the returns by their ex ante volatility.

Figure 3 shows the t-Stats from a pooled regression with standard errors clustered by time (monthly level) for the same h as before, only focusing on the sign of the past return. We observe only positive signs for the first 12 months and negative signs for the next 14 months, showing the same return continuation and then reversal as Figure 2. This is in accordance with the findings of Moskowitz et al. (2012). However, our regression shows positive t-Stats between months 27 and 50, where the results of Moskowitz et al. (2012) are primarily negative. These observations are interesting, as our results point to a more long-term return continuation while the findings of Moskowitz et al. (2012) show more long-term reversals. As mentioned previously, this could be explained by the difference in data. In addition, we believe that the strong growth in especially equities and commodities after 2009, as shown in Figure 11, could somewhat explain this difference. However, neither our observations nor the observations of Moskowitz et al. (2012) in this period are statistically significant.

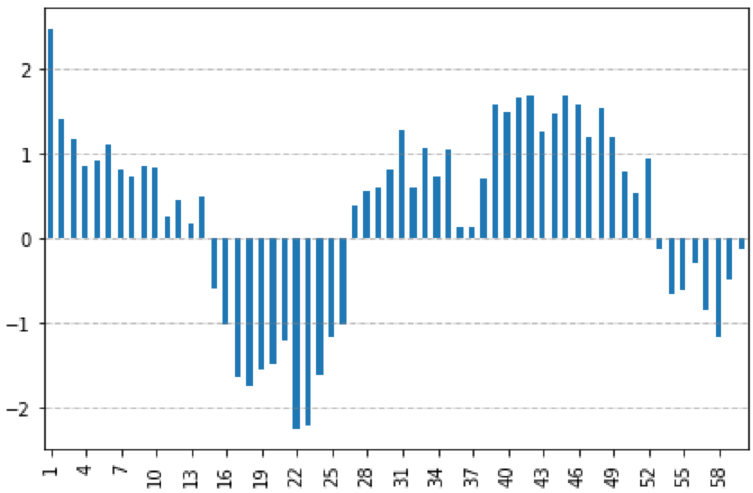

Figure 3: T-Stats for all asset classes with sign of return as predictor

Fig.3. The figure shows the time series predictability across all assets. We regress the monthly return of each instrument on its own lagged return over different time lengths, $\frac{r_t^t}{\sigma_{t-1}^t} = \alpha + \beta_h * sign(r_{t-h}^s) + \varepsilon_t^s$. In this regression, we use the sign of the lagged return as a predictor, scaling returns by their ex ante volatility to make meaningful comparisons across assets. Sample period is January 1985 to December 2021.

We also look at the individual predictability for each asset class, using both the lagged return, (5), and the sign of the lagged return,(6), as predictor. The results are illustrated in Figures 12 and 13, which are Appendix B. We do not find anything contrary when studying each asset class individually.

Our findings from both regression specification (5) and (6) show that the predictability of the TSMOM strategy is partly statistically significant. This result is somewhat contrary to the findings of Huang et al. (2020), as they reported strong evidence supporting no predictability. Looking at our results, we find evidence of some predictability, especially when looking at the same sample period as Moskowitz et al. (2012), with six out of the first 13 months in the look-back period being statistically significant on a 5% significance level. This could be explained by persistence in the return of the past 12 months, as Li and Yu (2012) show. Moreover, when increasing the sample period until December 2021, Figure 2 illustrates a decreasing trend, with only two out of the first 13 months showing statistically significant predictability. This trend could be related to the findings of McClean and Pontiff (2016), reporting lower predictability in the returns of publication-informed trading, and especially trading on anomalies heavily exploited by hedge funds. Momentum is one of the most researched market anomalies the last decade, with the research of Moskowitz et al. (2012) later being supported by Asness et al. (2013), Hurst et al. (2014), and Levine and Pedersen (2016). Furthermore, the number of hedge funds and other sophisticated investors that have started to pursue simple trend-following strategies has been ever-increasing since 1970 (Pedersen, 2015). This tendency points to the fact that being heavily researched and exploited by large institutional investors might have lowered the predictability of time series momentum over the last decade. The findings of Cotter and McGeever (2018) support the decrease in predictability, showing a significant diminishing effect of the momentum anomaly after 2007 in the U.K.

In terms of return predictability, two conclusions emerge from the results. First, we find statistically significant return predictability when looking at the same sample period as Moskowitz et al. (2012). This can be explained by return persistence in the past 12 months (Li and Yu, 2012). Second, we see that when extending the sample period, we observe lower predictability, pointing towards a diminishing effect of the TSMOM strategy.

Nevertheless, as we find statistical significant return predictability both when looking at the sample period of Moskowitz et al. (2012) and our sample period, this violates thew weak form of market efficiency (Fama, 1970). The results are therefore more in line with the research of Shiller (2003), as he argues that markets do not reflect all information, and that return predictability is possible in the medium to long term. To further assess the efficiency of the market, we evaluate the strategy's performance.

6.2 Performance of Time Series Momentum

Figure 4 shows the cumulative excess return for the diversified time series momentum strategy plotted against the cumulative excess return of a diversified passive long position in all instruments. As the figure shows, the diversified TSMOM strategy outperforms the diversified passive long portfolio. However, in terms of Sharpe ratios, the TSMOM strategy generates an annualized Sharpe ratio of 0.75, barely beating the passive portfolio's Sharpe ratio of 0.73. Both Sharpe ratios are statistically significant from zero on a 1% significance level.

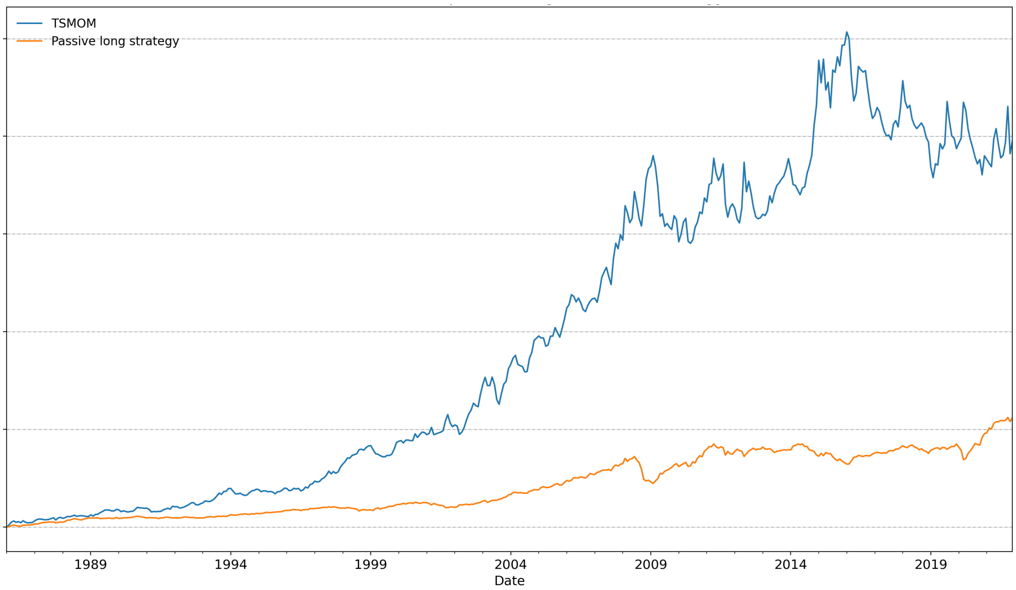

Figure 4: Time series momentum compared to a passive long strategy

Fig.4. The relative performance of our TSMOM strategy compared to a diversified passive long strategy. Plotted are the cumulative excess return of the diversified time series momentum strategy and cumulative excess return of the passive long position with equal weight in each instrument. Sample period is from January 1985 to December 2021.

We see that the strategy generates large profits in the last quarter of 2008. This period represents the peak of the Global Financial Crisis. Furthermore, the TSMOM strategy suffers losses in quarter three of 2008, as the strategy is still long in many instruments due to the 12-month look-back period. In the last quarter, the price movements have caused the strategy to be short in many instruments, generating significant profits as all markets except bonds continued to fall dramatically. We further see that the TSMOM strategy incurred significant losses when the financial crisis ended in the second quarter of 2009. Due to the look-back period of 12 months, the strategy was still short most of the instruments, and as the market started to rise in the second quarter of 2009, the strategy suffered losses. The same trends can be observed in the second quarter of 2020, which is the start of the Covid-19 pandemic. In March 2020, the equity indices on average fell approximately 20%, and we also see a sizeable drop in commodities, shown in Figure 11. After the substantial drop, the asset classes started to rise in the third quarter. The observations illustrate that our strategy performs well during a crisis and worse right before and after. This outcome is in line with what Pedersen (2015) argues, as sharp reversals will make a trend-following strategy incur losses as it does not manage to adapt quickly enough.

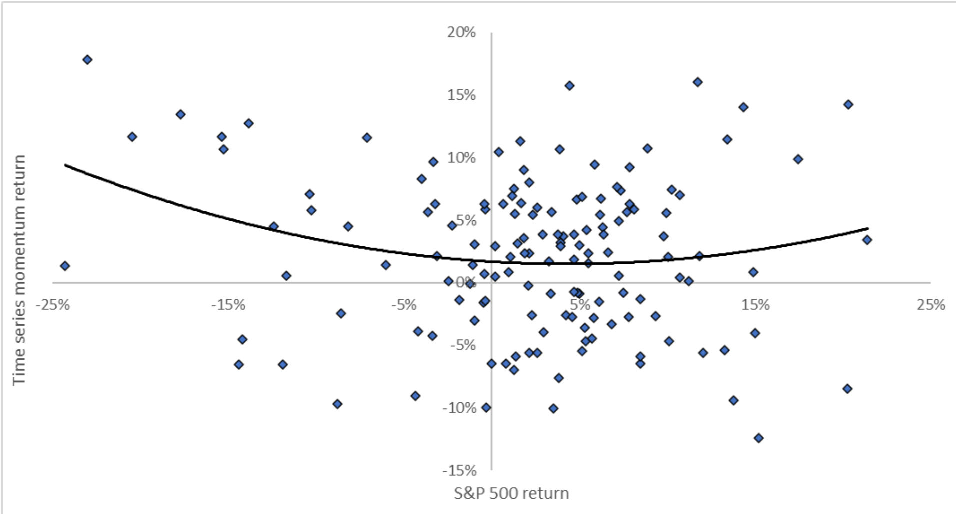

Figure 5: Time series momentum smile

Fig.5. The time series momentum smile. The quarterly returns of the TSMOM strategy are plotted against the returns of the S&P 500. As the figure visualizes, the TSMOM strategy performs best in extreme markets, i.e., when the market has high absolute returns, while generating less returns in flat markets. This creates a "smile". Sample period is January 1985 to December 2021.

Figure 5 emphasizes the discussion above. The figure plots the returns of TSMOM against the returns of the S&P 500. As one can see, the returns of TSMOM are the highest during the most immense movements in the S&P 500. This result indicates that the strategy delivers its highest profits during extreme markets while having lower profits during normal market conditions. TSMOM strategies generate profits because they go long when the market has a large upswing, and short when the market crashes, as shown by Fung and Hsieh (2001). Following the argumentation of Moskowitz et al. (2012), this suggests that the average positive returns from TSMOM are most likely not compensation for "crash risk", but rather the fact that during extreme market events, the economy goes from normal to bad. This makes the TSMOM go short the more risky assets, and then when the economy goes from bad to worse, the strategy generate profits.

An interesting observation is that the strategy performs very poorly after 2016. The cumulative return decreases from the height of approximately 2600% to approximately 1900%, a significant decrease. One hypothesis is this is due to sharp market reversals, making the TSMOM strategy go long when it should have been short, and vice versa. Another hypothesis is that the momentum effect has started to evaporate. As discussed, we find lower return predictability when using the full sample. Our findings, therefore, give even more support to the findings of McClean and Pontiff (2016) and Cotter and McGeever (2018), as they argued for lower return predictability in exploited anomalies, and the momentum effect diminishing, respectively.

6.2.1 Sharpe Ratio

We analyze the strategy's performance in terms of Sharpe ratio to further evaluate the presence of the momentum anomaly. Figure 6 reports each instrument's annualized gross Sharpe ratio. As the figure shows, all 55 instruments contribute positively to the time series momentum's return. We further find that 43 out of 55 Sharpe ratios are statistically different from zero on a 5% significance level, while 45 are statistically different from zero on a 10% significance level. The 2-year U.S. treasury generates the highest Sharpe ratio, with a strategy Sharpe ratio of 0.98. This result is closely followed by the S&P 500, generating a strategy Sharpe ratio of 0.71. We also observe that, on average, commodities generate a lower Sharpe ratio than the other asset classes. This outcome is most likely due to the commodities' high volatility, as visualized in Table 1.

Our findings are in accordance with Moskowitz et al. (2012). Their study found that 49 instruments are statistically different from zero on a 5% level, which is six more than our result. Regarding the Sharpe ratios, we observe that the 2-year U.S. treasury also generates the highest Sharpe ratio in their study, but that the remaining results somewhat differs. We see that, on average, our Sharpe ratios are slightly lower than what is reported by Moskowitz et al. (2012). As previously discussed, our findings have pointed toward a decrease in the predictability of time series momentum over the last decade. The lower average Sharpe ratio is in line with these results, giving a rational explanation for the underperformance of our strategy compared to the strategy of Moskowitz et al. (2012).

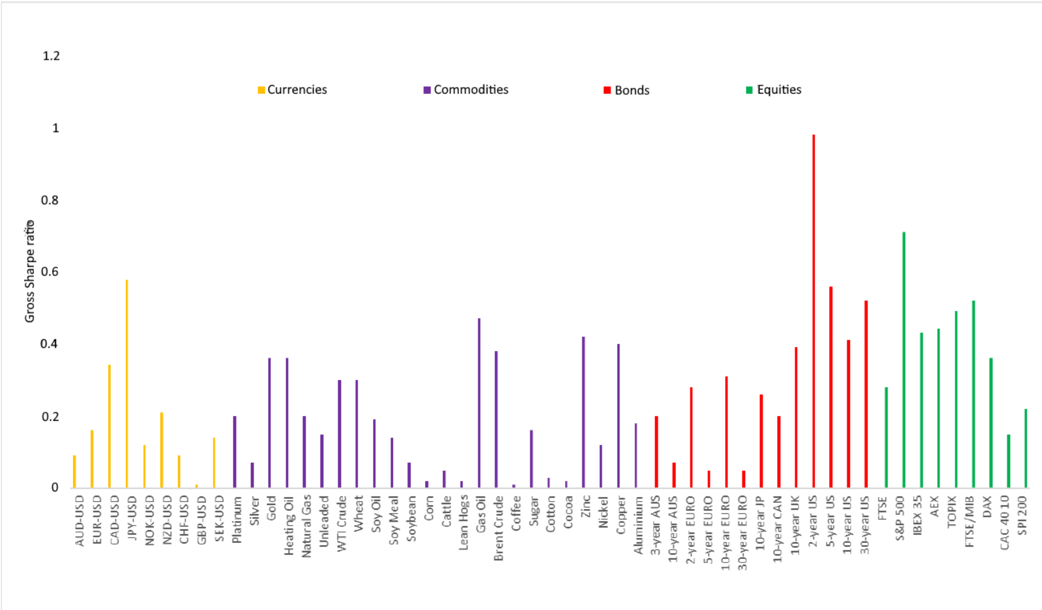

Figure 6: Sharpe ratio of TSMOM by instrument

Fig.6. The annualized Sharpe ratio of the TSMOM for each instrument. The Sharpe ratio is calculated by using monthly returns divided by the monthly volatility and then annualized. To test whether the Sharpe ratio is statistically different from zero we use a t-Test to test the mean of all instruments. Sample period is January 1985 to December 2021.

6.2.2 Alpha and Loading on Risk Factors

We evaluate the risk-adjusted performance of the time series momentum strategy using the Fama-French-Carhart Four-Factor Model, following the steps of Moskowitz et al. (2012). We regress the excess return of the TSMOM strategy on the excess return of the factors. These are the stock market MKT, the size factor *SMB*, the value factor *HML*, and the cross-sectional momentum factor *UMD*. We obtain the following regression:

$$r_t^{TSMOM} = \alpha + \beta_1 * MKT_t + \beta_2 * SMB_t + \beta_3 * UMD_t + \beta_4 * HML_t + \epsilon_t \quad (7)$$

The results are presented in Panel A of Table 2. As one can see, the TSMOM delivers a statistically significant alpha with respect to the mentioned factors of 0.63% per month. This finding states that the strategy creates value when risk-adjusting for the Carhart Four-Factor model. We see that the strategy loads negatively on both *SMB* and *HML*, but neither is statistically significant. Furthermore, the regression shows that TSMOM loads heavily on the cross-sectional momentum factor, *UMD*. This is not surprising, as the cross-sectional momentum factor focuses on relative performance among a set of assets, going long the top tier and short the bottom tier. The UMD-factor is statistically significant on a 1% significance level. Lastly, we observe that the strategy loads significantly on the market proxy on a 5% significance level.

When comparing to Moskowitz et al. (2012), we see that our findings are approximately the same. They find negative and insignificant loading on the SMB and HML factors, and heavy and significant loading on the UMD factor. As Moskowitz et al. (2012) control for Carhart Four-Factors, they find that the market coefficient is statistically significant on a 10% level. However, Moskowitz et al. (2012) find a monthly alpha of 1.58% compared to our alpha of 0.63%. Looking back at Figure 5, we see that our strategy performs poorly after 2016, with several large drawdowns. This performance could explain the value destroyed and we will further examine this in section 6.4.2.

However, as we mention in Section 5.3, we do not assess the Carhart Four-Factor to measure the exposure of all asset classes, as these factors primarily explain movements in the stock market. We, therefore, choose to also control for exposure to the bond market, *BOND*, and the commodity market, *GSCI*. We obtain the following regression:

$$
\begin{aligned}
r_t^{TSMOM} = \alpha + \beta_1 * MKT_t + \beta_2 * BOND_t + \beta_3 * GSCI_t + \\
\beta_4 * SMB_t + \beta_5 * UMD_t + \beta_6 * HML_t + \epsilon_t
\end{aligned}
\tag{8}
$$

The results from the regression are presented in Panel B of Table 2. Here we observe several intriguing results. First, we see that the exposure to the market proxy, *MSCI World*, is not significant on a 5% level anymore. Second, we see that the loading on *SMB* and *HML* still are insignificant, while the loading on UMD is still quite large and significant. However, what is most interesting is the TSMOM strategy's loading on the bond market. We observe that the excess return of the strategy loads extensively and significantly on the *BOND*-factor. This is interesting, as this implies that the returns from the bond market is covaries with the returns of our strategy.

Panel A: Regression specification (7)

	MSCI	SMB	HML	UMD	Intercept
Coefficient	0.0969	-0.0825	-0.0577	0.3292	0.0063
(t-Stat)	(2.382)**	(-1.458)	(-0.922)	(8.435)***	(3.7)***

Panel B: Regression specification (8)

	MSCI	SMB	HML	UMD	BOND	GSCI	Intercept
Coefficient	0.0707	-0.0350	-0.0490	0.3148	0.7701	0.0084	0.0044
(t-Stat)	(1.717)*	(-0.624)	(-0.798)	(8.257)***	(5.046)***	(0.281)	(2.60)***

Panel C: Regression specification (9)

	BOND	UMD	Intercept
Coefficient	0.8108	0.3059	0.0045
(t-Stat)	(8.475)***	(5.435)***	(2.684)***

Table 2: Risk-adjusted performance

Tab.2. The table shows the risk adjusted performance of the TSMOM strategy. The performance of the strategy is evaluated using regression specification (7), (8) and (9). The significance level of the t-Stat is specified using "*", where * equals that the observation is statistically significant on a 10% level, ** equals that the observation is statistically significant on a 5% level and *** equals the observation being statistically significant on a 1% level. The corresponding t-Stat for the different significance level are 1.645, 1.96, and 2.576, respectively. Sample period is January 1985 to December 2021. As the table visualizes, the strategy generates a statistical significant alpha on a 1% level when controlling for all three regression specifications.

The covariation with the bond market could be surprising, but when looking back at Figure 6, one must remember that the 2-year U.S. treasury generated the highest Sharpe ratio among the securities in the strategy. We also see that several bonds generate a relatively high Sharpe ratio. Therefore, the observation is not surprising when adding that all the Sharpe ratios generated by bonds are statistically different from zero. At last, we observe that the strategy's monthly alpha is now 0.44% or 5.28% annualized, and is still statistically significant on a 1% significance level. This result implies that when additionally controlling for exposure to the bond and commodity markets, the strategy still generates a statistically significant alpha.

If we remove all insignificant observations, we are left with the following equation:

$$r_t^{TSMOM} = \alpha + \beta_1 * BOND_t + \beta_2 * UMD_t + \epsilon_t \tag{9}$$

The final regression from specification (9) shows all significant variables when risk-adjusting the excess return of the TSMOM strategy. As Panel C in Table 2 shows, the returns of the strategy heavily load on both the *BOND*- and *UMD*-factor. When controlling for all significant variables, the strategy generates a statistically significant alpha of 0.45% per month or 5.4% annualized. This result is, as mentioned, somewhat lower than the alpha of Moskowitz et al. (2012) and underlines our previous findings of lower return predictability, but also illustrates that a simple trend-following strategy generate abnormal returns in our sample period.

Our findings in section 6.2, section 6.2.1, and section 6.2.2 all points in the opposite direction of the efficient market hypothesis of Fama (1970). Fama (1970) stated that even in the weakest form of market efficiency, simple trend-following strategies could not generate abnormal returns as the strategy is based on historical prices. However, our results show evidence that a strategy like our time series momentum strategy can generate abnormal returns. The cumulative return and the Sharpe ratio of the strategy outperform a long passive portfolio in the same instruments, and, as we show in the previous paragraph, the strategy generates a statistically significant alpha of 5.28% annualized. As we discuss, this is more in line with the research of Shiller (2003), stating that it is possible to predict return in the medium to long term. At the same time, we find overwhelming confirmation suggesting lower return predictability in the last decade. As Pedersen (2015) stated, the market must be so inefficient that investors can be compensated for their costs and risk through superior performance, but also so efficient that the returns do not encourage the entry of new managers or additional capital. The lower return predictability after 2009 points towards that the market has become more efficient, which is further supported by the findings of McClean and Pontiff (2016) and Cotter and McGeever (2018). Our results therefore support the efficiently inefficient hypothesis of Pedersen (2015), as we see significant, but decreasing, return predictability of the momentum effect. To further analyze these results, we have look at the performance of the time series momentum strategy after 2009.

6.3 Performance of TSMOM Strategy After 2009

To verify our findings of lower return predictability after 2009, we analyze the relative performance of the strategy between 2009 and 2021. Figure 7 shows the cumulative return of the TSMOM strategy after 2009 compared to a diversified passive long portfolio. As illustrated, the TSMOM strategy performed poorly after 2009, and is actually outperformed by the passive long strategy when comparing cumulative returns. In terms of Sharpe ratio, the difference is even more significant, with the TSMOM strategy generating an annual Sharpe ratio of 0.25, compared to a Sharpe ratio of 0.45 for the passive long strategy. This further supports the findings of McClean and Pontiff (2016) and Cotter and McGeever (2018), and is also in accordance with the efficiently inefficient hypothesis of Pedersen (2015), as it seems like extensive research and trading might have evaporated the momentum anomaly.

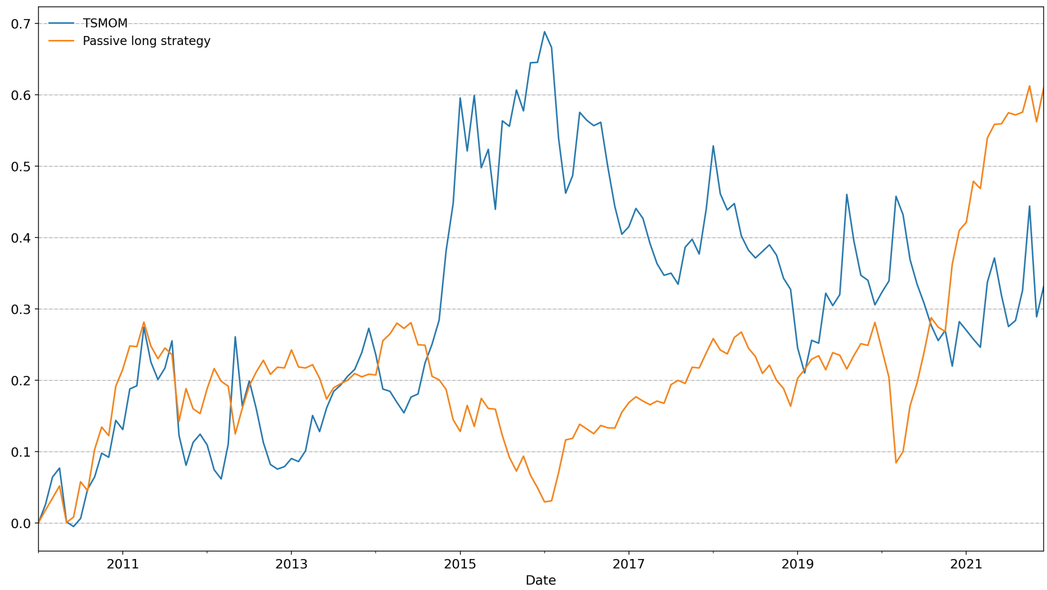

Figure 7: TSMOM cumulative return between 2009 - 2021

Fig.7. Performance of TSMOM strategy in subperiod 2009-2021, compared to a passive investment with equal weight in all instruments. In terms of cumulative return, the strategy is heavily outperformed by the passive market portfolio.

To validate our findings from Figure 7 we evaluate the risk-adjusted performance of the TSMOM strategy, using regression specification (7), (8) and (9). Table 3 illustrate the results.

Panel A: Regression specification (7)

	MSCI	SMB	HML	UMD	Intercept
Coefficient	0.0915	-0.1111	-0.329	0.6887	0.0001
(t-Stat)	(1.056)	(-0.799)	(0.219)	(6.203)***	(0.034)

Panel B: Regression specification (8)

	MSCI	SMB	HML	UMD	BOND	GSCI	Intercept
Coefficient	0.1608	-0.0576	0.1613	0.6610	0.7433	-0.079	-0.0018
(t-Stat)	(1.609)*	(-0.413)	(1.00)	(5.892)***	(1.759)*	(-1.089)	(-0.549)

Panel C: Regression specification (9)

	BOND	UMD	Intercept
Coefficient	0.6191	0.6258	-0.0008
(t-Stat)	(1.626)	(6-218)***	(-0.236)

Table 3: Risk-adjusted performance between 2009 and 2021

Tab.3. The table shows the risk adjusted performance of the TSMOM strategy. The performance of the strategy is evaluated using regression specification (7), (8) and (9). The significance level of the t-Stat is specified using "*", where * equals that the observation is statistically significant on a 10% level, ** equals that the observation is statistically significant on a 5% level and *** equals the observation being statistically significant on a 1% level. The corresponding t-Stat for the different significance level are 1.645, 1.96, and 2.576, respectively. Sample period is January 2009-December 2021. As the table visualizes, the strategy performs badly in this period, generating a negative, though insignificant, alpha when controlling both for regression specification (8) and (9).

Table 3 presents several interesting results. Both Panels A, B, and C illustrate that the alpha has decreased substantially. In two out of three regressions, the strategy generates a negative alpha, with the third observation being approximately equal to zero. Even though non of the alpha's from the regressions are statistically significant, these findings clearly show that the TSMOM strategy did not generate abnormal returns in this period, and further indicates that it actually destroyed value. Comparing with our results in Table 4, the covaration with the *BOND*- and *UMD*-factor is still high, but the significance of the observations is, in general, lower. The *HML*-factor now shows a positive covariation, but is still insignificant. Our observations are in line with the results of Cotter and McGeever (2018), and emphasize our previous suggestion of a decrease in the return predictability of time series momentum. To check the robustness of our, we control the strategy's performance in two additional subperiods to confirm that the sample size does not explain our insignificant results.

6.4 Controlling Other Subperiods

Table 4 shows the performance of the TSMOM strategy in three different subperiods in addition to the full sample. The strategy produces a statistically significant alpha in all periods except January 2009 to December 2021. This shows that the insignificant performance of the strategy in this period is not explained by the small sample size, and underline our findings of the momentum anomaly diminishing. On the basis of the robustness check in this section and the results presented in Section 6.3, we conclude that the performance of the momentum strategy has significantly decreased in the last decade, further supporting the research of McClean and Pontiff (2016) and Cotter and McGeever (2018). Following the decrease in performance, we find it meaningful and very interesting to see if using drawdown control as a risk management tool could add value to the strategy in terms of cumulative return, Sharpe ratio, and risk-adjusted returns.

	1985-1997	1997-2009	2009-2021	Full sample
Alpha from regression (7)	0.75***%	1.04***%	0.01%	0.63%***
Alpha from regression (8)	0.69**%	0.8***%	-0.18%	0.44%***
Alpha from regression (9)	0.59***%	0.77***%	-0.08%	0.45%***
Sharpe Ratio	1.11	1.10	0.25	0.75

Table 4: Performance in all subperiods including the full sample

Tab.4. The table shows the risk adjusted performance and the Sharpe ratio of the TSMOM strategy in all subperiods in addition to the full sample. The risk adjusted performance of the strategy is evaluated using regression specification (7), (8) and (9). The significance level of the t-Stat is specified using "*", where * equals that the observation is statistically significant on a 10% level, ** equals that the observation is statistically significant on a 5% level and *** equals the observation being statistically significant on a 1% level. The corresponding t-Stat for the different significance level are 1.645, 1.96, and 2.576, respectively. Sample period is January 2009-December 2021. As the table visualizes, the strategy performs badly in the last subperiod, generating a negative, and insignificant, alpha when controlling both for regression specification (8) and (9).

6.5 Improving the Strategy

In this section we will analyze if drawdown control could improve our strategy. First, we analyze when the most significant drawdowns in our strategy occur. Second, we analyze the implications of using drawdown control as a risk management tool. To further assess if using drawdown control enhances the strategy's performance, we analyze the relative performance with and without risk management.

6.5.1 Measuring Drawdown

We define a drawdown as any period when the cumulative return of the strategy is lower than its current high water mark. Figure 8 visualizes the drawdown of the strategy. As one can see, the most significant drawdowns are experienced after 2008, with the largest happening in 2019, amounting to a loss of 28.3%.

Looking back at Section 6.3, we see a connection between the large drawdowns in this period and the poor performance of the TSMOM strategy in the same period. As Figure 8 shows, the strategy starts to generate negative returns after 2016 and never manages to bounce back.

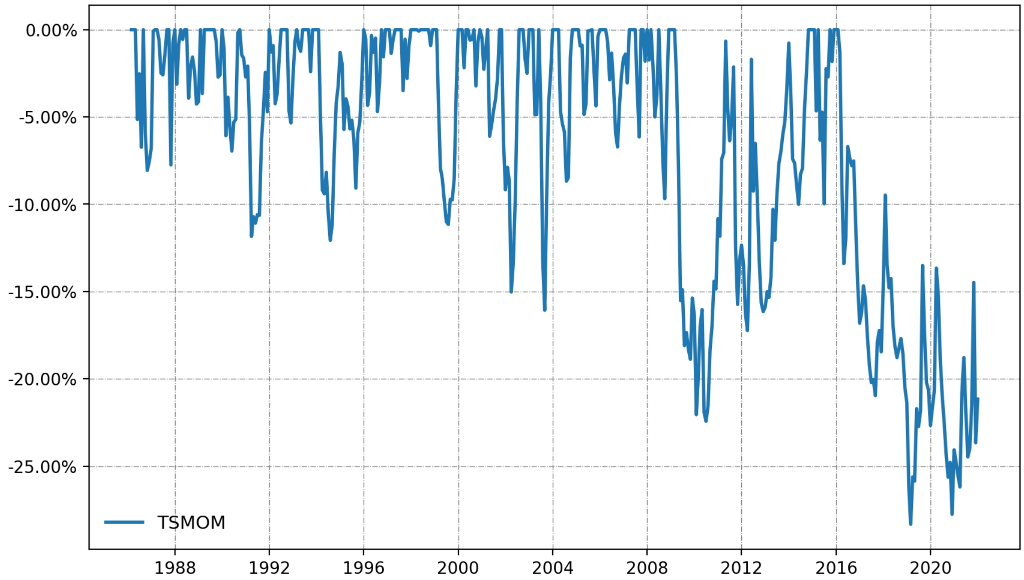

Figure 8: Drawdown of TSMOM strategy

Fig.8. The figure shows the drawdowns of the TSMOM strategy by measuring when the cumulative return of the strategy is below its high water mark. As illustrated, the largest drawdowns are experienced after 2009. Sample period is January 1985 to December 2021.

Based on the visualization of drawdowns, we see a potential for improving the strategy. Being able to minimize drawdowns will make the strategy recover from its losses more quickly, ultimately making it continue to increase its high water mark.

6.5.2 Using Drawdown as a Risk Management Tool

As Chekhlov et al. (2005) describe, an account may be closed if a drawdown breaches 20%. Looking at Figure 8, we see that our strategy has several drawdowns exceeding 20%. Even for a superior hedge fund, several drawdowns of more than 20% could result in a margin call. Especially the period after 2016 would have been difficult to sustain, with a period of approximately five years without reaching a new high water mark. This would at least lead to unhappy investors and might even make the investors try to withdraw their money, creating liquidity problems (Gray and Vogel, 2013).

Following the research of Chekhlov et al. (2005), we define our maximum acceptable drawdown as 20%. We then obtain the following equation:

$$DD \leq 20\% \tag{10}$$

Equation (10) states that the strategy's drawdown shall never exceed 20%. To accomplish this, we need to reduce risk before the drawdown reaches 20%. If we start reducing risk when the drawdown is 20%, this would violate Equation (11), and we would need to unwind all positions immediately. Unwinding all positions would generate substantial transaction cost, and also equals that the investor is left without have any position in the market. This is often unacceptable for large institutional investors. On the basis of this we create a "signal" for when we start reducing the risk. Whenever the strategy's drawdown is higher than 15%, we start unwinding positions to scale down the risk. Further, we do not unwind more than 50% of our positions, ensuring that we always have a stake in the market.

Figure 9 displays the drawdown of the TSMOM strategy after implementing drawdown control. As one can see, the maximum acceptable drawdown of 20% is never breached, with the new maximum drawdown being 18.9%. This is a reduction of approximately 33% from the previous maximum drawdown, or ten percentage points. We also observe that the strategy now manages to bounce back to a new high water mark in 2021, an achievement that is not feasible without risk management. This might imply that drawdown control manages to reduce some of the tail risk associated with trend-following strategies, as Gray and Vogel (2013) describes.

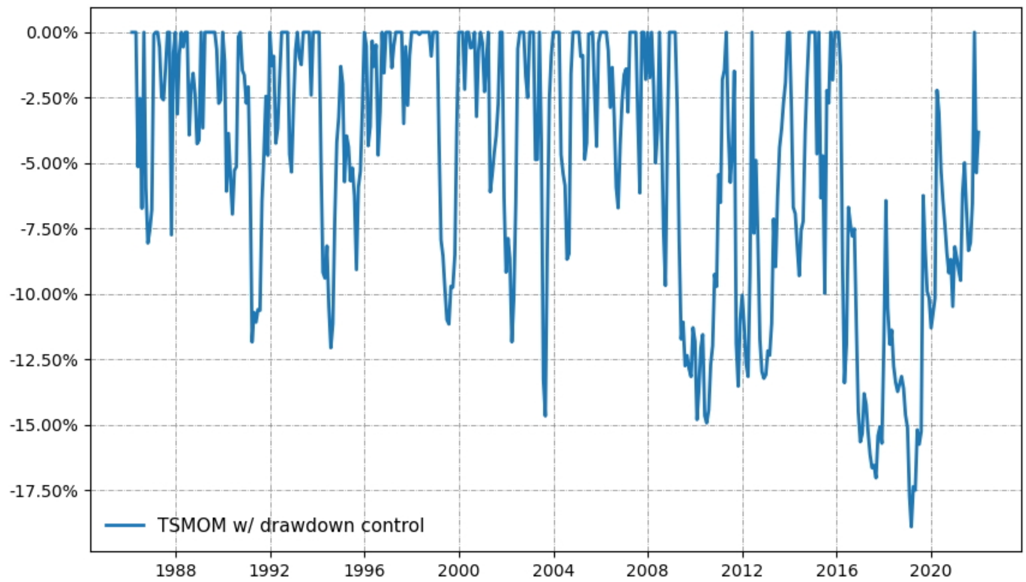

Figure 9: Drawdown control of TSMOM strategy

Fig.9. The figure displays the drawdown of the TSMOM strategy after the use of drawdown control as a risk management tool. The drawdown is measured as whenever the cumulative return of the strategy goes below its high water mark. Sample period is January 1985 to December 2021 .

6.6 Relative Performance of TSMOM with Drawdown Control

To assess the relative performance of the TSMOM with drawdown control, we first look at the cumulative return of the strategy, comparing it to the TSMOM without drawdown control and the passive long strategy. When we study Figure 10, we see that in terms of cumulative return, the TSMOM strategy with drawdown control outperforms the original TSMOM strategy. As the figure illustrate, the improved TSMOM strategy generates a significantly higher return than the replication of Moskowitz et al. (2012) when using the full sample period.

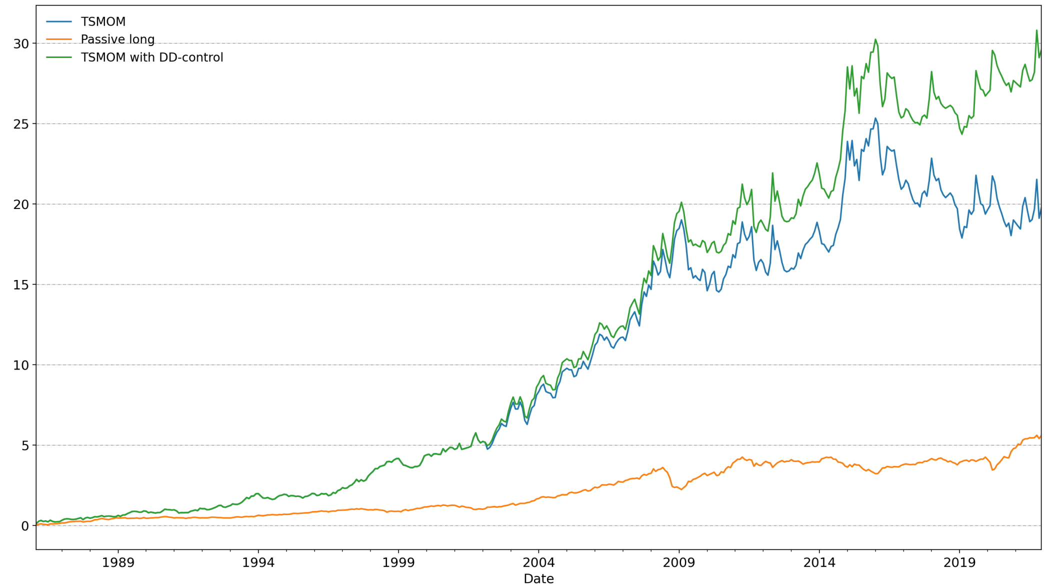

Figure 10: Cumulative return of TSMOM with drawdown control

Fig.10. The figure visualises the cumulative return of the TSMOM strategy with and without drawdown control, also including a equally-weighted passive long strategy. As displayed, the TSMOM with drawdown control heavily outperforms the two other strategies, showing the importance of risk management. Transaction costs are not included. Sample period is January 1985 to December 2021.

The difference becomes immense in the period after 2016, which is reasonable, considering the lower return predictability we find after 2009. In terms of performance measures, Table 5 reports the annualized Sharpe ratio for the TSMOM, TSMOM with drawdown control, and the passive long strategy. All Sharpe ratios are statistically significant on a 1% significance level, and as the table illustrates, the TSMOM strategy with drawdown control generates a substantially higher Sharpe ratio than the other strategies. However, this result is expected, as we implemented drawdown control as a risk management tool. Figure 10 clearly illustrate that the volatility in the strategy is reduced, while the return is increased.

	Annualized mean	Annualized volatility	Sharpe Ratio
TSMOM	10.0%	13.3%	0.75
TSMOM with drawdown control	12.6%	11.8%	1.07
Passive long	6.0%	8.2%	0.73

Table 5: Annualized Sharpe ratio for TSMOM with and without drawdown control

Tab.5. The table shows the annual return, volatility and Sharpe ratio of for the TSMOM with and without drawdown control, in addition to a passive strategy starting with an equal position in each instrument. The sample period is January 1985 to December 2021, and all observations is statistically significant different from zero on a 1% significance level, using a t-Test.

When further evaluating the performance of TSMOM with drawdown control, we evaluate the strategy's alpha. To compare it with the TSMOM without drawdown control, we run a regression using regression specification (8) and (9).

	MSCI World	SMB	HML	UMD	BOND	GSCI	Intercept
Panel A: Comparison of strategies using regression specification (8)							
TSMOM							
Coefficient	0.0707	-0.0350	-0.0490	0.3148	0.7701	0.0084	0.0044
(t-Stat)	(1.717)*	(-0.624)	(-0.798)	(8.257)***	(5.046)***	(0.281)	(2.60)***
TSMOM with drawdown control							
Coefficient	0.0692	-0.0271	-0.0551	0.2940	0.77009	0.0166	0.0051
(t-Stat)	(1.746)*	(-0.503)	(-0.933)	(8.011)***	(5.246)***	(0.574)	(3.117)***

	BOND	UMD	Intercept
Panel B: Comparison of strategies using regression specification (9)			
TSMOM			
Coefficient	0.8108	0.3059	0.0045
(t-Stat)	(8.475)***	(5.435)***	(2.684)***
TSMOM with drawdown control			
Coefficient	0.8047	0.2865	0.0052
(t-Stat)	(8.235)***	(5.596)***	(3.210)***

Table 6: Risk-adjusted performance with and without drawdown control

Tab.6. The table shows the performance of the TSMOM strategy. In this table, we illustrate the risk adjusted return of the TSMOM strategy with and without drawdown control using regression specification (7) and (8). The significance level of the t-Stat is specified using "*", where * equals that the observation is statistically significant on a 10% level, ** equals that the observation is statistically significant on a 5% level and *** equals the observation being statistically significant on a 1% level. The corresponding t-Stat for the different significance level are 1.645, 1.96, and 2.576, respectively. Sample period is January 2009-December 2021.

Panel A of Table 6 shows the comparison of the risk loading of the TSMOM with and without drawdown control using regression specification (8). In general, there are few differences between the risk loading of the two strategies. Both strategies load heavily on the *BOND*- and *UMD*-factor. This is, however, not a surprise, as we have not altered the strategy's positions, but decreased the size when drawdowns breached 15%. Nonetheless, what we find interesting is that we see an increase in the monthly alpha of approximately seven basis points when adding drawdown control to the strategy. This increase amounts to an annualized alpha of 6.12%, compared to 5.28% for the strategy without drawdown control. We further observe that the significance of the observation also increases.

Panel B of Table 6 compares the two strategies when only controlling for factors significant on a 5& level. We observe the same trend as in Panel A. The strategy with drawdown control generates a monthly alpha that is seven basis points higher, and the significance of the alpha increases. The result shows that our findings are robust, underlining that using drawdown control not only manages the risk by reducing the risk, but also generates abnormal returns.

Adding drawdown control increases our strategy's Sharpe ratio and generates a higher abnormal return than the strategy without risk management. Furthermore, we see that the additional value created by the drawdown control outweighs the lower return predictability after 2009. This ultimately creates a superior time series momentum strategy than presented by Moskowitz et al. (2012). We have not considered the transaction costs that would have occurred from the drawdown control. This factor will lower the total return of the superior strategy. However, considering that the instruments in our study are among the most liquid in the world, we believe our results are still robust and show the advantages of using drawdown control to manage the risk of a trend-following strategy.

7 Conclusion

This thesis researches if a time series momentum strategy manages to generate abnormal returns, investigating the presence of the momentum anomaly in financial markets. Further, the thesis researches if using drawdown control as a risk management tool enhances the time series momentum strategy's performance. The research question of the thesis is:

> *Is the momentum anomaly still present in global financial markets, and is it possible to improve a time series momentum strategy by adding drawdown control?*

We find evidence for the presence of the momentum anomaly in our sample period. The TSMOM strategy outperforms a diversified passive long strategy, with a Sharpe ratio of 0.75 compared to a Sharpe ratio of 0.73. The TSMOM strategy also generates a statistically significant monthly alpha of 0.44% per month when controlling for exposure to the Carhart Four-Factor model and the bond and commodity markets. These findings suggest that a simple trend-following strategy based on historical prices actually creates value, which is contrary to the weak form of market efficiency presented by Fama (1970), but aligned with the findings of Moskowitz et al. (2012). However, we find overwhelming proof of a decrease in the return predictability of the TSMOM strategy over the last decade. We find statistical evidence stating that the return predictability decreases significantly when extending the sample period from December 2009 to December 2021. When controlling the TSMOM strategy from 2009 to 2021, we find that the strategy is outperformed by a passive long strategy, with a Sharpe ratio of 0.25 compared to a Sharpe ratio of 0.45, respectively. Interestingly, when controlling for exposure to the mentioned risk factors, the strategy generates a negative alpha. Even though the alpha is statistically insignificant, the result implies that the TSMOM strategy destroyed value during this period. These findings are aligned with the research of McClean and Pontiff (2016) and Cotter and McGeever (2018), finding lower return predictability and a diminishing effect of the momentum anomaly in the U.K. Our finding also somewhat support Huang et al. (2020) criticism of Moskowitz et al. (2012), reporting insufficient statistical evidence for the return predictability of TSMOM. Our results suggest that the effect of the momentum anomaly is diminishing, possibly due to extensive research publication and a rapid increase of sophisticated investors exploiting the anomaly. This points toward the efficiently inefficiently hypothesis presented by Pedersen (2015), stating that financial markets are just so inefficient that it is possible to generate abnormal returns, but also so efficient that when anomalies are extensively exploited, their superior performance diminishes.

We further find that when adding drawdown control to a TSMOM strategy, the performance enhances substantially. The strategy with drawdown control generated a significant Sharpe ratio of 1.07, compared to the strategy without, generating a Sharpe ratio of 0.75. We find that drawdown control increases the monthly alpha by seven basis points, and also increases the observation's statistical significance. Not surprisingly, the TSMOM strategy experienced the most significant drawdowns after 2009. In this period, the drawdown control creates value because it manages to limit losses from sharp trend reversals, and further generate returns from identifying short-term counter trends (Pedersen, 2015).

Future research could focus on exploring the diminishing effect of the momentum anomaly, testing other look-back and holding periods. Further, one could also research if one can observe the same evaporation of return predictability when using a cross-sectional momentum strategy. In addition, future research could also focus on different risk management tools that could enhance the a trend-following strategy's performance.

A Appendix: Data Sources

A.1 Country Equity Indices

For Country Equity Indices, Moskowitz et al. (2012) have futures from nine developed equity markets: ASX SPI 200 (Australia), CAC 40 10 (France), DAX (Germany), FTSE/MIB (Italy), SP 500 (U.S.), TOPIX (Japan), AEX (Netherlands), IBEX 35 (Spain), and FTSE 100 (U.K.). We retrieve the data on equity index futures from Bloomberg and Datastream. However, we only have access to futures prices for the full sample length for FTSE, S&P 500, and AEX, so we use proxies for the remaining indices. As Moskowitz et al. (2012), we use the MSCI country-level index prior to the availability of the remaining futures returns.

A.2 Government Bond Futures

We use bond futures from 13 developed bond markets. These are 3-year Australian, 10-year Australian, 2-year Euro, 5-year Euro, 10-year Euro, 30-year Euro, 10-year Canadian, 10-year Japanese, 10-year U.K., 2-year U.S., 5-year U.S., 10-year U.S., and the 30-year U.S. We obtain the data from Bloomberg and Datastream. As Table 1 shows, we only manage to retrieve data for the full sample length for 10-year Australian, 10-year U.K., 10-year U.S., and the 30-year U.S. Moskowitz et al. (2012) use JP Morgan country-level bond index returns as their proxy to returns prior to the availability of future returns. BI Norwegian Business School does not have access to the JP Morgan country-level bond index. Moskowitz et al. (2012) end their time series in December 2009, while we have data until December 2021. The total amount of data is therefore approximately the same, and we regard our data as satisfactory for the replication. We therefore choose not to prolong the data with a proxy. Further, to be consistent with Moskowitz et al. (2012), we scale the daily returns of our bond futures to a constant duration of two years for 2- and 3-year bonds, four years for 5-year bonds, seven years for 10-year bonds, and twenty years for 30-years bonds.

A.3 Currency Forwards

For the foreign exchange, we have a base of 12 cross-currency pairs. This is AUD-NZD, AUD-USD, EUR-JPY, EUR-NOK, EUR-SEK, EUR-CHF, EUR-GBP. JPY-AUD, GBP-USD, USD-EUR, USD-CAD, and USD-JPY. Moskowitz et al. (2012) have an investment universe of currency forwards covering ten exchange rates. The universe includes Australia, Canada, Germany spliced with the Euro, Japan, New Zealand, Norway, Sweden, Switzerland, United Kingdom, and the United States of America. For simplicity, Moskowitz et al. (2012) choose to look at the first nine currencies vs. USD. These nine forward exchange rates underline the movements in the 12 cross-currency pairs. Unfortunately, we do not have access to spot- and forward rates from Citigroup, so we retrieve data from Bloomberg and Datastream. We use forward exchange rates from October 1990 to present-day to calculate currency returns. Before October 1990, we use spot exchange rates as a proxy for forward rates to calculate the returns.

A.4 Commodity Futures

For commodities, we use 24 different commodity futures gathered from seven different exchanges. The data on Aluminum, Copper, Nickel, and Zinc are from London Metal Exchange (LME), Brent Crude, Gas Oil, Cotton, Coffee, Cocoa, and Sugar are from the Intercontinental Exchange (ICE), Live Cattle and Lean Hogs are from Chicago Mercantile Exchange (CME), Corn, Soybeans, Soy Meal, Soy Oil, and Wheat are from Chicago Board of Trade (CBOT). Further, WTI Crude, RBOB Gasoline spliced with Unleaded Gasoline, Heating Oil, and Natural Gas are from New York Mercantile Exchange (NYMEX), Gold and Silver are from New York Commodities Exchange (COMEX), and Platinum from Tokyo Commodity Exchange (TOCOM). We obtain the futures prices from Bloomberg. Unfortunately, we do not manage to obtain returns for all commodities back to 01.01.1985, but as Table 1 illustrates, this is also the case for Moskowitz et al. (2012). We therefore decide to implement the different commodities in the strategy as their data becomes available.

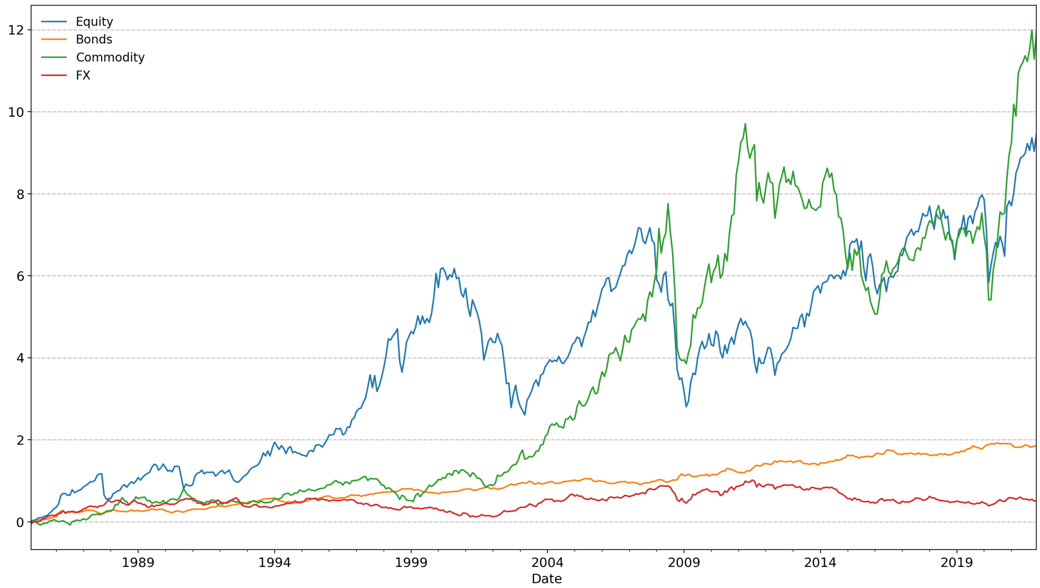

Figure 11: Cumulative returns for each asset class

The figure shows the cumulative return of a portfolio with equal weight in each instrument within each asset class. The strategy is passive and long only. Sample period is January 1985 to December 2021.

B Appendix: Individual Asset Class Return Predictability

B.1 Using lagged return as predictor

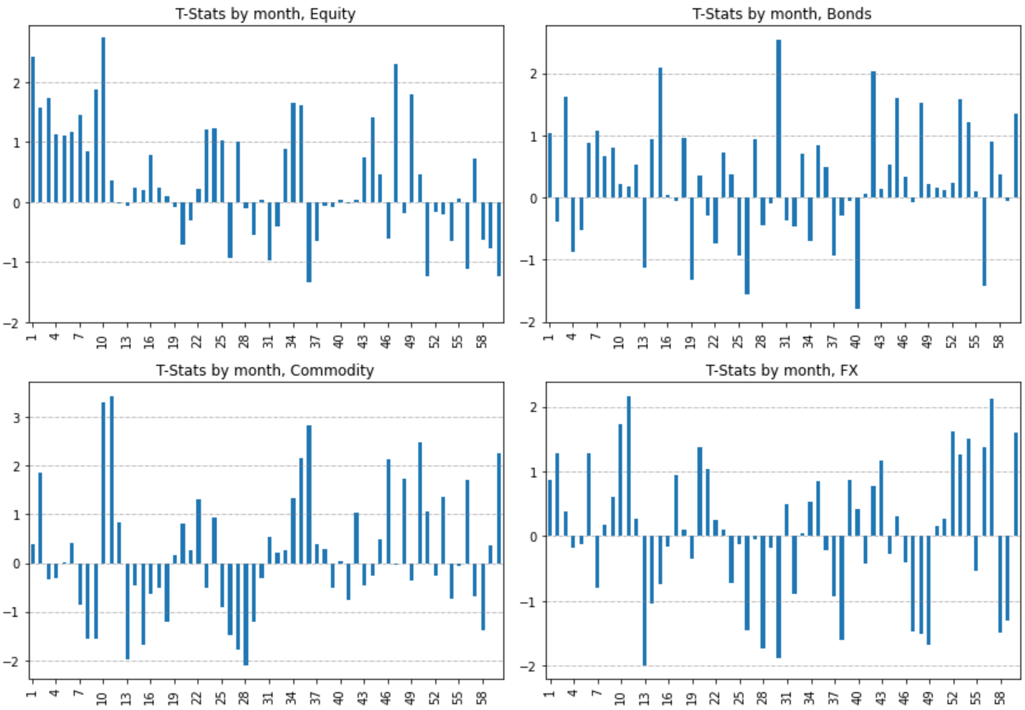

Figure 12: T-Stat for each asset class

The figure shows the time series predictability for each asset class. We regress the monthly return of each instrument on its own lagged return over different time lengths, $\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h \frac{r_t^s}{\sigma_{t-h-1}^s} + \varepsilon_t^s$. In this regression, we use the size of the lagged return as a predictor, scaling returns by their ex ante volatility to make meaningful comparisons across assets. Sample period is January 1985 to December 2021. We find that all classes more or less follow the same trends as Figure 2, with one-to-12-month positive t-Stats followed by reversals in month 13. We also see that each asset class have a reversal in month 26.

B.2 Using sign of return as predictor

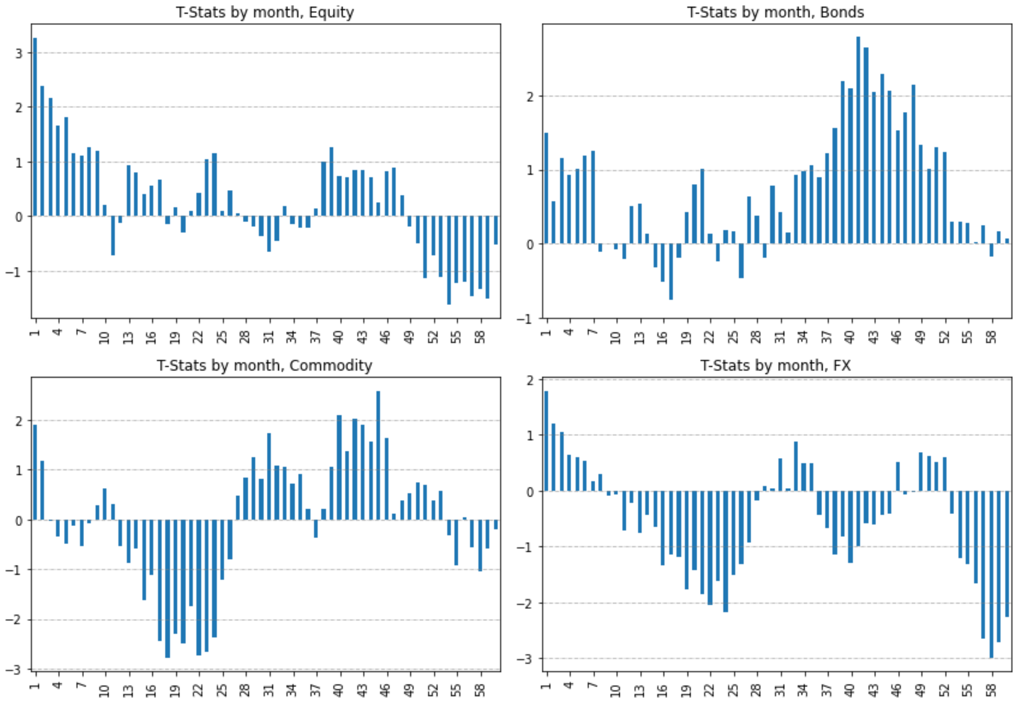

Figure 13: T-Stat for each asset class

The figure shows time series predictability across each asset class. We regress the monthly return of each instrument on its own lagged return over different time lengths, $\frac{r_t^t}{\sigma_{t-1}^t} = \alpha + \beta_h * sign(r_{t-h}^s) + \varepsilon_t^s$. In this regression, we use the sign of the lagged return as a predictor, scaling returns by their ex ante volatility to make meaningful comparisons across assets. Sample period is January 1985 to December 2021. We observe that equities, bonds, and currencies follow the same trends as Figure 3 for the first 12 months, while the predictability of commodities vary. It is, however, only equities that have significant t-Stats in this period. Furthermore, the different asset classes all show a reversal in month 13.

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