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Hedge Fund Replication through Trend-Following

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Management Summary

While the use of managed futures funds has increased in the past, the actual investment strategy remains to some extent a secret to outside investors. In recent years, managed futures have often been associated with trend-following. Indeed, several studies have shown that trend-following strategies can significantly replicate the returns of these funds. However, it is not known exactly what type of trend-following strategies are used in practice.

The current state of the literature shows that time series momentum, which only considers the past return of the underlying asset itself, largely explains the returns of managed futures. However, recent academic evidence has shown that the weighting coefficients of speculators' returns in futures markets do not resemble the weightings of time series momentum strategies. They appear to be more similar to the more dynamic moving average crossover strategies. On this basis, it was hypothesized that moving average crossover signals can better replicate the returns of managed futures than time series momentum. Related to this is the research question of which trend-following signals most clearly explain managed futures returns.

To answer this research question, three widely adopted trend-following strategies were first developed and analyzed. These strategies consisted of time series momentum and different moving average crossovers. They were then categorized into short-, medium-, and long-term trend signals. In terms of underlying data, the focus was on liquid futures contracts and currency pairs. Comparing all signals with conventional passive investments in different markets and common risk factors, there is a positive significant alpha left for each signal and each considered trend horizon. This result is evidence of the presence and importance of momentum for the three different trend following strategies and also shows low exposure to common investment factors.

In separate regressions in this thesis, moving average crossover strategies were found to be more capable of explaining managed futures returns than time series momentum strategies. A subsequent analysis of different approaches to risk assessment also revealed that managed futures incorporate a type of widely used RiskMetrics approach that has not been previously discussed in the literature.

Based on the previous scientific finding that the distinction between long- and short-only trend signals can better replicate the returns of managed futures, this separation was also analyzed. However, since the statistical regressions were strongly affected by multicollinearity between these split signals, a relaxed lasso procedure was applied to obtain a representative and stable set of trend-following signals that can accurately describe the returns of managed futures. The derived signal selection showed promising explanatory values and furthermore novel robust values in the predictability of managed futures returns. Furthermore, it was possible to identify certain investment preferences of managed futures.

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List of Abbreviations

CMA	Investment pattern factor
COM	Center of mass
CTA	Commodity trading advisor
$EWMA^{fast}$	Exponentially weighted fast moving average
$EWMA^{slow}$	Exponentially weighted slow moving average
HML	Value factor
MACROSS	Moving average crossover
MA^{fast}	Fast moving average
MA^{slow}	Slow moving average
MOM	Momentum factor
RMW	Profitability factor
SMB	Size factor
TSMOM	Time series momentum

1 Introduction

Trend-following is a centuries-old multipurpose approach that is being studied extensively in the financial world for the past few decades. Nowadays, trend-following is considered among the classic investment styles, and it is especially popular in futures markets. The investors most directly focused on trend-following investing are *managed futures* hedge funds and *commodity trading advisors* (CTAs). The terms "managed futures" and "CTAs" are often used interchangeably. However, for greater clarity, managed futures can be described as the investment style and CTAs can be understood as the professional managers who create diversified futures portfolios (CME Group, 2022).

1.1 Problem Definition and Relevance

Although the use of managed futures funds has increased in the past, the actual investment strategy remains, to a certain extent, a mystery to outside investors. In recent years, managed futures funds have often been associated with trend-following. Several studies have also shown that the returns of these funds can be replicated to a considerable degree using trend-following strategies. However, it is not known exactly what type of trend-following approaches are used in practice. The level of understanding of managed futures hedge funds is also interesting because of the current global economic situation. The unstable political environment, inflation, and rising interest rates following a prolonged period of low interest rates have put pressure on various asset classes and investment strategies. Many investors are, therefore, seeking alternative investments. Hedge funds, including those that follow the managed futures investment strategy, are among these alternatives.

1.2 Objective

This thesis contrasts different trend-following strategies for hedge funds. There are many trading signals that can be used for trend-following. However, as described in the previous section, it is not known which signals are used professionally. Therefore, the objective of this work is to find out which trend-following signals are most likely to be used by these funds.

1.3 Research Question

Based on the problem and the objective, this thesis addresses the following research question:

– *Which trend-following signals most significantly explain managed futures returns?*

In addition to this research question, this thesis examines different risk approaches to trading signals and exposure to specific futures contracts that could explain the returns of CTAs.

1.4 Limitations of the Study

Since trend-following strategies are mainly associated with managed futures, this thesis investigates only the returns of this category of funds. The daily values of various managed futures indices during a predetermined period are considered as a proxy for managed futures returns. Although fees, especially transaction fees, are an essential part of the investment strategy of CTAs, they are not considered in this work. In other words, the trading strategies developed in this thesis have been simplified by not considering fees so that the focus is on declaring the trading signals used by hedge funds.

1.5 Structure

This section provides a brief overview of the structure of this thesis, which is designed to answer the research question. The present work is divided into three parts.

Following the introduction, a literature review is provided. This review involves analyzing the available scientific knowledge and its development. The intent is to critically examine the current state of knowledge and relate it to the goal of this thesis, namely, the replication of managed futures trading signals.

Subsequently, the empirical analysis of this thesis is presented, and the corresponding results are reported. In this chapter, the trading strategies are constructed first, and then the different risk frameworks and the influence of each asset are analyzed. After that, a selection of the best trading signals is made.

Finally, a conclusion is formulated that is aimed at answering the research question posed at the beginning, and possible implications for further research are identified.

2 Literature Review

This part of the thesis focuses on the relevant literature on trend-following. Section 2.1 reviews the literature on trend-following and its development. Section 2.2 provides an overview of prior and recent studies that have examined the use and underlying mechanisms of time series momentum.

2.1 Trend-Following

Trend-following as an investment style has been around for a long time. Approximately 200 years ago, the classical economist David Ricardo suggested paying attention to trends with his statement to "cut short your losses" and "let your profits run on." This quotation, now known as a traditional trading rule, was first printed in a work by Grant (1837, p. 56). However, there is still a debate in financial academia about market efficiency that suggests that trend-following strategies should not work. Some studies find arguments against these strategies while other results are in favor of them.

The literature initially focused on *momentum* strategies, which look at the relative performance of securities on a cross-sectional basis, finding that securities that outperformed their peers over the past 3 to 12 months continue to outperform them on average over the next month. Momentum has been found in all kinds of markets over the years and evaluated accordingly.[1] To construct such a strategy, an investor looks at a basket of assets and buys those that have performed the best over a given period while selling those that have performed the worst, regardless of how well or poorly the assets have performed. Jegadeesh and Titman (1993) referred to such a portfolio as a "winners minus losers portfolio." Later, Moskowitz et al. (2012) presented global evidence on *time series momentum* (TSMOM). TSMOM is a timing strategy that uses exclusively past returns on individual assets and is distinct from the cross-sectional momentum strategies explained earlier. Due to its high relevance for the empirical analysis in Chapter 3, TSMOM will be discussed in more detail in the next section.

---

[1] For U.S. equities (Jegadeesh & Titman, 1993) and international equities (Fama & French, 2012; Rouwenhorst, 1998), in the currency markets (Burnside et al., 2011; Menkhoff & Taylor, 2007; Shleifer & Summers, 1990), commodity markets (Erb & Harvey, 2006; Gorton et al., 2013; Miffre & Rallis, 2007; Shen et al., 2007), futures (Pirrong, 2005), and essentially across all markets (Asness et al., 2013).

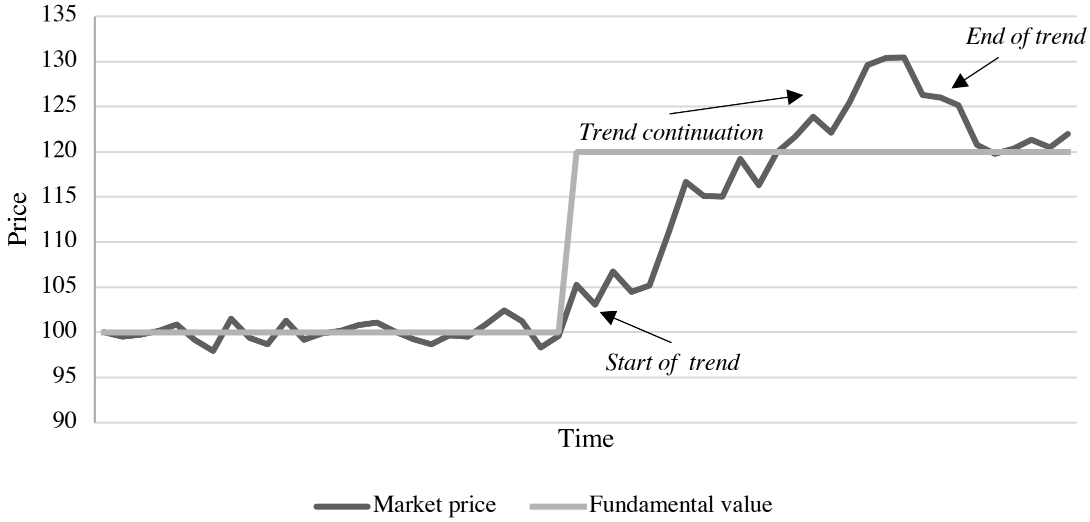
2.2 Time Series Momentum

In academia, TSMOM has only recently been popularized through the work of Moskowitz et al. (2012). The TSMOM strategy is simple to implement because it solely involves buying assets with positive past returns and selling assets with negative past returns, regardless of the relative performance that has been the focus of the momentum-related work mentioned above. Moskowitz et al. (2012, pp. 236–237) revealed that a portfolio of all futures contracts considered provided a significant alpha of 1.58% per month with respect to the MSCI World Index and standard factors of Fama and French (1993) and Carhart (1997), and an alpha of 1.09% when calculated using the MSCI World Index and the long-short value and cross-sectional momentum factors of Asness et al. (2013) across all asset classes. Furthermore, Moskowitz et al. (2012, pp. 240–241) regressed TSMOM returns diversified across all instruments on cross-sectional momentum returns diversified across the same instruments. They found a significant relation between the two and, in addition, a significant alpha of 0.76% per month not captured by the cross-sectional strategy. A further distinctive feature is that the TSMOM returns of Moskowitz et al. (2012, pp. 229–231) were found in liquid futures markets, and these futures showed no correlation between their abnormal returns and measures of liquidity or sentiment. In comparison, previous research on momentum discovered that stocks that generate large momentum gains are also stocks with significant trading costs and that these costs are sufficient to offset the momentum gains (Lesmond et al., 2004). Similarly, Korajczyk and Sadka (2004) found that relatively poorly performing stocks tend to be small companies with low liquidity and short-selling restrictions.

2.2.1 Underlying Mechanism of Times Series Momentum

The economic rationale underlying trend-following strategies is illustrated in Figure 1 by using an example asset based on the life cycle of a trend presented by Hurst et al. (2013, pp. 44–46). An initial underreaction to a shift in fundamental value allows a trend-following strategy to respond before the new information is fully reflected in prices. The trend then progresses beyond fundamentals because of herding effects, which ultimately lead to a reversal. Each of the three phases of this stylized trend is discussed below, as is the related literature.

FIGURE 1: LIFE CYCLE OF A TREND



Notes: This figure is based on the illustration of Hurst et al. (2013, pp. 44–46).

2.2.1.1 Start of the Trend

In the example shown in Figure 1, a catalyst—a positive earnings announcement, a supply shock, or a shift in demand—causes the value of an asset to change (Hurst et al., 2013, p. 44). The shift in fundamental value is immediate, as shown by the solid light-gray line in Figure 1. The market price represented by the dark-gray line rises as a result of the catalyst, but it initially underreacts and thereby continues to rise gradually. There are many researched theories that account for the observed underreaction of prices after a fundamental change in value:

i. <u>*Anchor-and-insufficiency adjustment:*</u> Edwards (1968) and Tversky and Kahneman (1974, pp. 1128–1130) find evidence that people anchor their price beliefs to historical price data and are slow to respond to new information. This price conservatism leads to an underreaction in prices (Barberis et al., 1998). There is also evidence that underreaction is caused by delay in the dissemination of news (Hong & Stein, 1999).

ii. <u>*The disposition effect:*</u> Shefrin and Statman (1985) and Frazzini (2006) observe that people tend to sell winners too early and hold losers for too long. They sell winners too early because they want to realize their gains. This creates a downward price pressure that slows the upward price adjustment to new positive information. On the other hand, people hold on to losers because it is "painful" to realize losses. They try to regain what they have lost. As a result, less willing sellers can prevent prices from being adjusted downward as quickly as they should.

iii. *Nonprofit Activities:* Central banks intervene in foreign exchange and bond markets to reduce the volatility of exchange rates and interest rates, which can slow down price adjustment to news (Silber, 1994). In addition, investors who mechanically rebalance their strategic asset allocation may be trading against the trend. For example, an investor who wants to own 60% stocks and 40% bonds will sell stocks and buy bonds when stocks have outperformed (Hurst et al., 2013, p. 45). In addition, Baltas and Kosowski (2013, p. 4) note that corporate hedging programs can also slow down price movements.

iv. *Frictions and slow flowing capital:* Frictional losses, delayed reactions by some market participants, and slow flowing arbitrage capital can also cause price discovery to decelerate and resurge (Duffie, 2010; Mitchell et al., 2007).

2.2.1.2 Trend Continuation

Once a trend has started, there are several other underlying phenomena that can extend the trend beyond the fundamental value:

i. *Herding and feedback trading:* There are many possible explanations for why prices exceed the fundamental value for a while. Bikhchandani et al. (1992) show that herding behavior is a phenomenon intrinsic to human nature to which investors are also predisposed. An asset that has performed well in a period is more attractive to new investors since others have been successful with it. Analysts in particular are susceptible to herding biases (Welch, 2000), as are investment newsletters (Graham, 1999). Another case of herding behavior occurs through feedback trading. Feedback traders are traders whose demand is based on the history of past returns rather than the expectation of future fundamentals (Cutler et al., 1990, p. 1). This behavior can also lead to overreaction and drive market prices above fundamentals (De Long et al., 1990; Hong & Stein, 1999).

ii. *Confirmation bias and representativeness:* Wason (1960) and Tversky and Kahneman (1974, pp. 1124–1127) provide evidence that people tend to look for information that confirms what they already believe and view recent price movements as representative of what will follow. This can lead to investors reallocating capital into assets that have earned money recently and, conversely, exiting assets that have declined, both of which cause the trend to continue (Barberis et al., 1998; Daniel et al., 1997).

iii. *Fund flows and risk management:* When investors withdraw funds from underperforming managers, those managers respond by reducing their underperforming positions, while outperforming managers receive inflows that increase buying pressure on their outperforming positions (Hurst et al., 2013, p. 45). In addition, some risk management strategies involve selling in down markets and buying in up markets to follow the trend. Hurst et al. (2013, p. 45) provide the example of an airline that might hedge against oil prices after a price increase, which in turn puts upward pressure on future prices. Consequently, such risk management practices can also create feedback loops (Garleanu & Pedersen, 2007).

2.2.1.3 End of the Trend

It is obvious that trends cannot last forever. At some point, prices go too far above the fundamental value, and when people realize this, prices return to the fundamental value and the trend eventually ends (Hurst et al., 2013, p. 45). Moskowitz et al. (2012, p. 233) find evidence of such exaggerated trends when returns reverse after more than one year of positive TSMOM returns. Such a long-term return reversal is also found in the cross-section of equities (De Bondt & Thaler, 1985) and in the cross-section of global asset classes (Asness et al., 2013). Hurst et al. (2013, pp. 45–46) conclude that the reversal of returns reverses only part of the initial price trend, implying that the price trend was caused partially by an initial underreaction, since that part of the trend should not reverse, and partially by a delayed overreaction, since that part does reverse.

2.2.2 Predictability of Returns and Trend Signs

TSMOM can only function if future returns can be forecasted by past returns, or at least if the sign of future returns can be predicted by past returns. Both Moskowitz et al. (2012, p. 233) and Baltas and Kosowski (2013, pp. 10–11) examine whether autocorrelation exists in their return series of various futures and find a strong relationship in overall returns between them. Moskowitz et al. (2012, p. 230) refer to the literature on autocorrelation of returns, which also identifies deviations from the random walk hypothesis, based on the finding of positive autocorrelation for shorter time horizons and reversals for periods longer than one year (Fama & French, 1988; Lo & MacKinlay, 1988; Poterba & Summers, 1988). While this literature focuses largely on U.S. and global equities, Cutler et al. (1991) examine a variety of assets, including real estate and collectibles. Positive autocorrelations in the short term and negative autocorrelations in the longer term are adequate preconditions for the trend described in the previous section.

In summary, TSMOM strategies should benefit from adequate short-term return forecasting capabilities and even forecasts of sign reversals in the long run, as assessed in the literature.

3 Empirical Research

This thesis follows the research design of Hurst et al. (2013), who proved that momentum can explain the returns of managed futures indices. They constructed a TSMOM strategy, based on the work of Moskowitz et al. (2012) described in Section 2.2, which involves buying assets when the return over a certain time series is positive and selling assets when the return over the period is negative. This strategy is in line with the fundamental concept that TSMOM is a simple trend-following strategy that involves buying an asset if it has a positive excess return over a certain retrospective horizon and going short otherwise. Hurst et al. (2013, p. 43) examined 1-month, 3-month, and 12-month look-back horizons and implemented the strategies over a liquid set of commodity futures, equity futures, currency forwards, and government bond futures. Their research revealed that TSMOM strategies had large correlations and high R^2 values with managed futures indices and individual manager returns, including the largest and most successful managers at that time. It was also demonstrated in a recent study by Boos and Grob (2022) that trend-following and momentum trading are indeed the predominant investment strategies of speculative traders in the commodity futures market. Furthermore, they showed the weighting coefficients of the daily returns of speculators in the past. When graphing these weighting coefficients, it can be seen that the weighting does not resemble the weighting of the TSMOM strategies, which was used by Hurst et al. (2013) to explain the returns of managed futures. The plots are more similar to the theoretical return weighting of *un-weighted* and *exponentially weighted moving average crossover* strategies described by Levine and Pedersen (2016). These two trend-following signals are described in more detail in Subsections 3.2.2 and 3.2.3.

Boos and Grob's (2022) finding that the weighting of past returns of commodity futures resembles more dynamic trend-following strategies suggests that a drawback of the Hurst et al. (2013) study is that it used only TSMOM signals to explain the returns of managed futures indices. Therefore, it can be hypothesized that dynamic crossover strategies are able to better replicate the returns of CTAs. Hence, this thesis aims to contribute scientifically to the field of hedge funds, which are classified as managed futures, based on the current state of knowledge and the described deficit.

This chapter describes the steps taken to find the most appropriate trend signals that most accurately explain managed futures returns. To begin with, the next section describes the data that are used for this thesis.

3.1 Data

The data include futures prices for 23 commodities, 19 stock indices, and 15 government bonds, as well as 10 currency pairs. Daily closing prices in US dollars were retrieved from Bloomberg over the time series from January 1999 to August 2022. However, the data availability of certain instruments started at a later stage. For all futures, the closing prices of the first generic futures were used. To get an accurate overview of currency pair trading, the Bloomberg Total Carry Return Index was used for each of the 10 currency pairs. In this research, the focus is on the most liquid instruments to avoid returns being affected by illiquidity or outdated prices and to better achieve an implementable strategy with significant trading volume. A detailed overview of all instruments is presented below in Table 1.

Commodities	**Equities**	**Bonds**	**Currencies**
Energy	*Americas*	*North/Latin America*	AUD/USD
WTI	Dow Jones mini	US ULTRA BOND	EUR/USD
Gasoline	S&P 500 mini	US LONG BOND	CAD/USD
Natural Gas	NASDAQ 100 mini	US 10YR ULTRA FUT	JPY/USD
Brent	S&P/TSX 60	US 10YR NOTE	NOK/USD
Crude	MEX IPC	US 5YR NOTE	NZD/USD
Grains	IBOVESPA	US 2YR NOTE	SEK/USD
Corn	*EMEA*	CAN 10YR BOND FUT	CHF/USD
Chicago Wheat	EURO STOXX 50	*Europe/Africa*	GBP/USD
Kansas Wheat	FTSE 100	EURO-BUXL 30Y BND	DKK/USD
Soybeans	CAC 40	EURO-BUND FUTURE	
Soybean Meal	DAX	EURO-BOBL FUTURE	
Soybean Oil	IBEX 35	EURO-SCHATZ	
Livestock	FTSE MIV	LONG GILT FUTURE	
Live Cattle	AEX	Eur-BTP Future	
Feeder Cattle	OMX STKH30	Euro-OAT Future	
Lean Hogs	SWISS MKT	*Asia/Pacific*	
Softs	*Asia/Pacific*	JPN 10Y BOND	
Sugar	NIKKEI 225 (OSE)		
Coffee	HANG SENG		
Cotton	CSI 300		
Cocoa	S&P/ASX		

Metals			
Gold			
Silver			
Platinum			
Copper			

TABLE 1: OVERVIEW OF CONSIDERED FUTURES CONTRACTS AND CURRENCY PAIRS
Notes: Supplementary information on these instruments can be found in Appendix A.

To test how accurately trend-following signals can explain managed futures, the daily returns of four managed futures indices were calculated using closing prices from Bloomberg. These four indices, which were used as proxies for managed futures returns, were:

Managed Future Index	Coverage start date	Coverage end date
HFRX Macro/CTA Index (1)	*March 31, 2003*	*August 31, 2022*
SG CTA Index (2)	*December 31, 1999*	*August 31, 2022*
HFRX Macro Systematic Diversified CTA Index (3)	*December 31, 2008*	*August 31, 2022*
SG CTA Mutual Fund Index (4)	*December 31, 2012*	*August 20, 2020*

TABLE 2: OVERVIEW OF MANAGED FUTURES INDICES THAT ARE USED AS PROXIES FOR CTA PERFORMANCE

3.2 Trend Signals

As a result of the finding described in the beginning of this chapter that rather unsophisticated TSMOM signals may not precisely describe the returns of managed futures, the work of Hurst et al. (2013) is now extended here to examine additional trading signals. In addition to the previously studied TSMOM, this thesis examines the unweighted moving average crossover, henceforth referred to as the *simple moving average crossover*, and the exponentially weighted moving average crossover to explain managed futures returns. Among these three categories of trend signals, different time horizons for each signal are also compared in this thesis. These horizons are set in such a way that they are mutually comparable and approximately correspond to a short-term, medium-term, and long-term trend sequence. In addition, in this thesis, the weights of each asset are rebalanced daily for each trend signal to account for trading frictions and minimize noise due to infrequent rebalancing. This approach is similar to that of Levine and Pedersen (2016, p. 61), while Hurst et al. (2013, pp. 46–47) rebalanced portfolios weekly and Moskowitz et al. (2012, p. 233) rebalanced them monthly.

After the three signal categories are analyzed individually, they are then contrasted as independent coefficients in a series of linear regressions in Section 3.3 to determine which signal provides the most accurate results in terms of explaining managed futures returns. In addition, this thesis explores different approaches to risk estimation to provide a more accurate understanding of how CTAs manage their risks. First, however, the trend signals are analyzed separately and then compared in the following subsections.

3.2.1 Time Series Momentum

In this subsection, the focus is on the TSMOM strategy used by Hurst et al. (2013) to explain the returns of various managed futures indices and specific managers. This model was based on the work of Moskowitz et al. (2012), in which they documented significant TSMOM in various futures classes. In terms of calculation, a traditional TSMOM return of an asset *s* with a look-back period of *n* days is defined as:

$$r_{t,t+1}^{TSMOM,s} = sign\left(r_{t-n,t}^{s}\right) * \frac{40\%}{\sigma_t^s} * r_{t+1}^{s}$$

$$sign(r_{t-n,t}^{s})\begin{cases} +1\ if\ r_{t-n,t}^{s} > 0 \\ -1\ if\ r_{t-n,t}^{s} < 0 \end{cases} \tag{1}$$

The first part of Equation 1 indicates whether the signal is long or short. Thus, *sign()* denotes a sign function, which in this case outputs the trade signal, which can take the values +1 or –1. The value of +1 implies a buy signal and –1 a sell signal. This signal is determined by the accumulated return over *n* days, calculated as the percentage change between the two prices.[2]

The second part of Equation 1 determines the weighting of the asset *s*. Each position (long or short) is sized to have an ex ante annualized volatility of 40%. As Kim, Tse, and Wald (2016, p. 104) identified, such volatility scaling is similar to the *risk parity approach* to asset allocation. For that matter, a risk parity portfolio is an equally weighted portfolio, where the weights are based on risk rather than the dollar amount invested in each asset (Kazemi, 2012, p. 21). The choice of a volatility of 40% was arbitrary, but it facilitated an intuitive comparison of the portfolio with other risk factors in the literature (Moskowitz

[2] It should be noted that arithmetic returns have been used throughout this thesis to allow for cross-sectional aggregation across assets.

et al., 2012, p. 236). Moskowitz et al. (2012) chose the annual volatility of 40% because it corresponds to the risk of an average individual stock.

In estimating the risk, volatility σ_t^s, Hurst et al. (2013) also used a method proposed by Moskowitz et al. (2012). The ex ante volatility σ_t^s of each instrument is calculated at each point in time using the exponentially weighted lagged squared daily returns. The daily variance $(\sigma_t^s)^2$ is therefore calculated for each futures contract *s* using the following model:

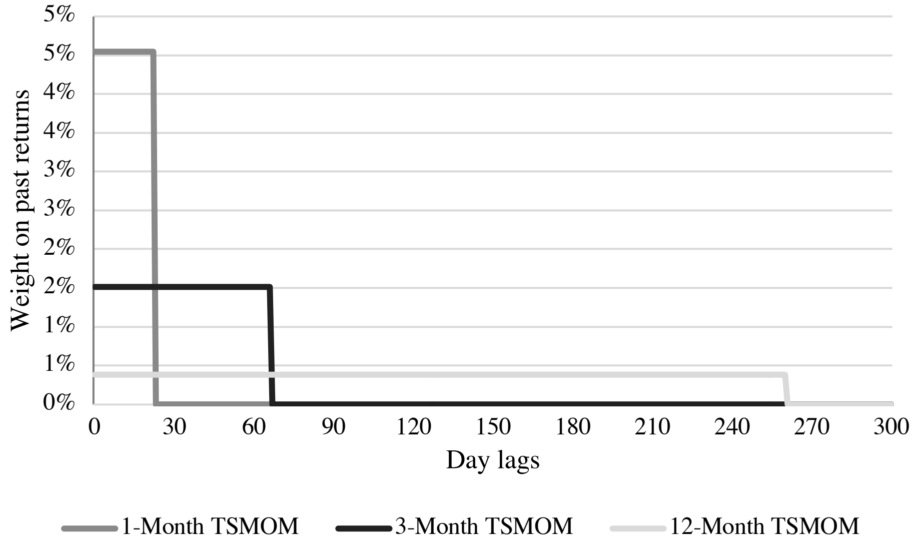
$$(\sigma_t^s)^2 = 261 \sum_{i=0}^{\infty} (1-\delta)\delta^i ({r^s}_{t-1-i} - \overline{{r^s}_t})^2 \tag{2}$$

The scalar 261 in Equation 2 scales the variance to be annual, and $\overline{{r^s}_t}$ is the exponentially weighted average return calculated in a similar way. The parameter δ is chosen so that the *center of mass* (COM) of the weights, given by $\sum_{i=0}^{\infty}(1-\delta)\delta^i i = \delta/(1-\delta)$, is equal to 60 days.

To conclude, in Equation 1, the trading signal is first determined by the cumulative return over the look-back period. Then, the signal is multiplied by the weight of the traded instrument based on the risk. And finally, as shown in the third part of Equation 1, it is multiplied by the next day's realized return. This is how the daily return of the TSMOM strategy is calculated.

Since TSMOM is based on historical returns, Figure 2 illustrates the dependence on past returns for these time horizons. As can be seen in this *return signature plot*, which is modeled after Levine and Pedersen (2016, p. 54), the past daily returns have an equal weighting, depending on the time horizon chosen for the TSMOM signal.

FIGURE 2: RETURN SIGNATURE PLOT OF TSMOM



Notes: This figure illustrates how much weight a TSMOM signal assigns to past returns. All TSMOM signals analyzed in this thesis are shown in this figure. This illustration is modeled on the approach of Levine and Pedersen (2016, p. 54).

Based on the methodology described above, which is the same as that of Hurst et al. (2013), except for the rebalancing frequency described earlier, TSMOM strategies with 1-month, 3-month, and 12-month look-back horizons are considered in this thesis, corresponding to short-, medium-, and long-term trend strategies.

3.2.2 Simple Moving Average Crossover

Moving average crossovers (MACROSS) is one of the commonly used technical trading rules. This strategy is expressed as a buy signal when the moving average of a short period falls above the moving average of a long period and as a sell signal when the reverse happens (Brock, Lakonishok, & LeBaron, 1992, p. 1735). According to Levine and Pedersen (2016, p. 52), the underlying idea is that a moving average of the short period captures recent average prices, while a moving average of a longer period captures where prices used to be. They refer to the two moving averages as the *fast moving average* (MA^{fast}) and *slow moving average* (MA^{slow}), respectively. Such a comparison of different price averages is illustrated in Figure 3 using the Dow Jones mini future as an example. Moving averages can be calculated in several ways. This subsection describes the procedure where the moving averages are equally weighted in each instance. This trading method will be referred to as a *simple moving average crossover* in the following to distinguish it from another MACROSS strategy described in Subsection 3.2.3.

FIGURE 3: SIMPLE MACROSS INDICATOR

Notes: This chart compares two equally weighted moving averages of the Dow Jones Mini future price with its market price. MA^{fast} uses a 12-day average while the MA^{slow} uses a 120-day average. Since the fast moving average at the end of the sample is above the slow moving average, an upward trend is apparent.

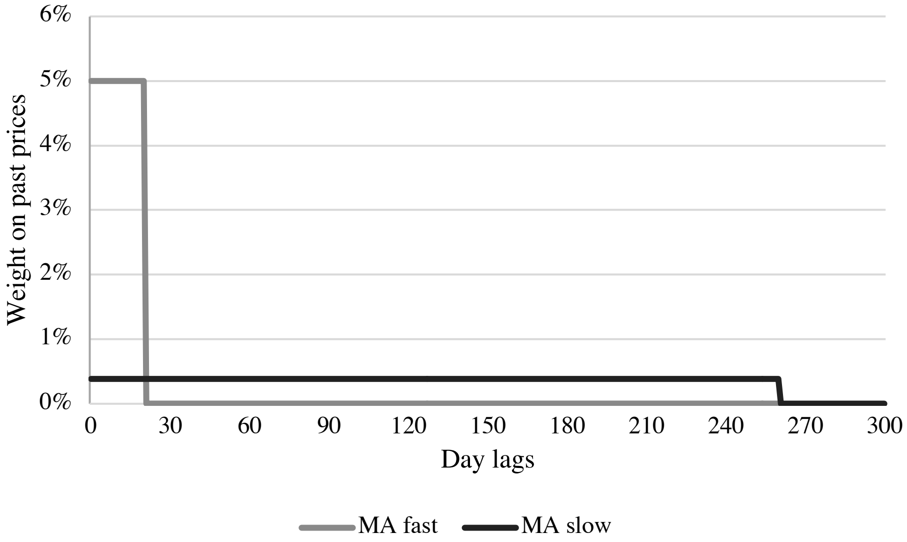
Mathematically formulated, the moving averages of a price P at time *t* are described as follows:

$$MA_t^{fast,s} = \sum_{i=0}^{\infty} w_i^{fast} * P_{t-i+1}^{s}$$

$$MA_t^{slow,s} = \sum_{i=0}^{\infty} w_i^{slow} * P_{t-i+1}^{s} \tag{3}$$

Levine and Pedersen (2016, p. 53) explain that moving averages can be computed using any weighting scheme w. However, the moving averages are equally weighted for each period in the simple MACROSS, as mentioned earlier. This is shown graphically in Figure 4, illustrating the dependence on past prices using an example MA^{fast} of 20 days and an MA^{slow} of 260 days.

FIGURE 4: PRICE SIGNATURE PLOT OF SIMPLE MOVING AVERAGES



Notes: This figure illustrates how much weight a moving average assigns to past prices. MA^{fast} uses a 20-day average, and MA^{slow} uses a 260-day average. This illustration is modeled on the approach of Levine and Pedersen (2016, p. 54).

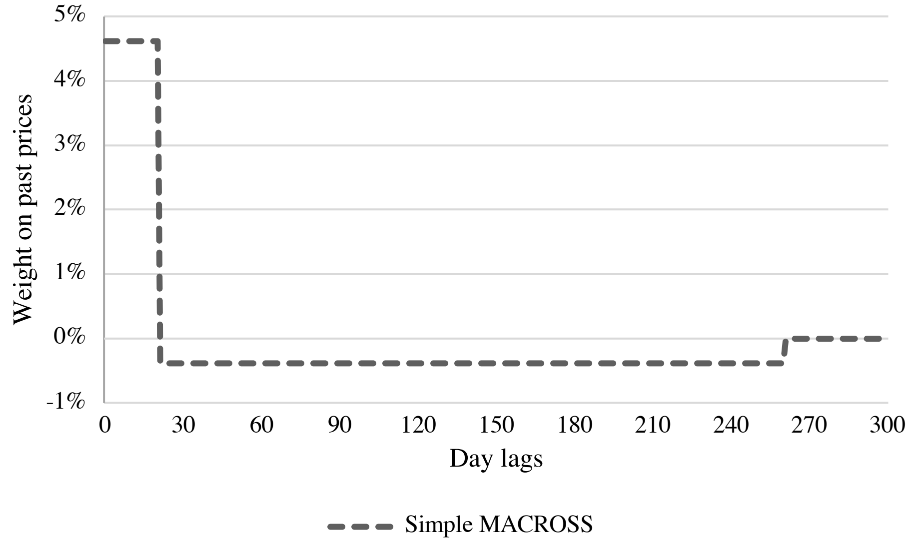
Since a MACROSS strategy considers which moving average is above the other moving average, the trading signal can be simplified and written as a difference between Equation 3 for each considered futures contract *s*:

$$MACROSS_t^s = MA_t^{fast,s} - MA_t^{slow,s}$$

$$MACROSS_t^s = \sum_{i=0}^{\infty} (w_i^{fast} - w_i^{slow}) * P_{t-i+1}^s \tag{4}$$

Therefore, Equation 4 produces a long signal when $MACROSS_t^s$ is positive and a short signal when $MACROSS_t^s$ is negative. Thus, in the simple MACROSS strategy, MA^{fast} minus MA^{slow}, the weighting of the recent prices is positive, but the weighting of the more distant prices is negative, and the weights eventually go to zero. This combination of the importance of past prices is depicted in Figure 5.

FIGURE 5: PRICE SIGNATURE PLOT OF SIMPLE MACROSS



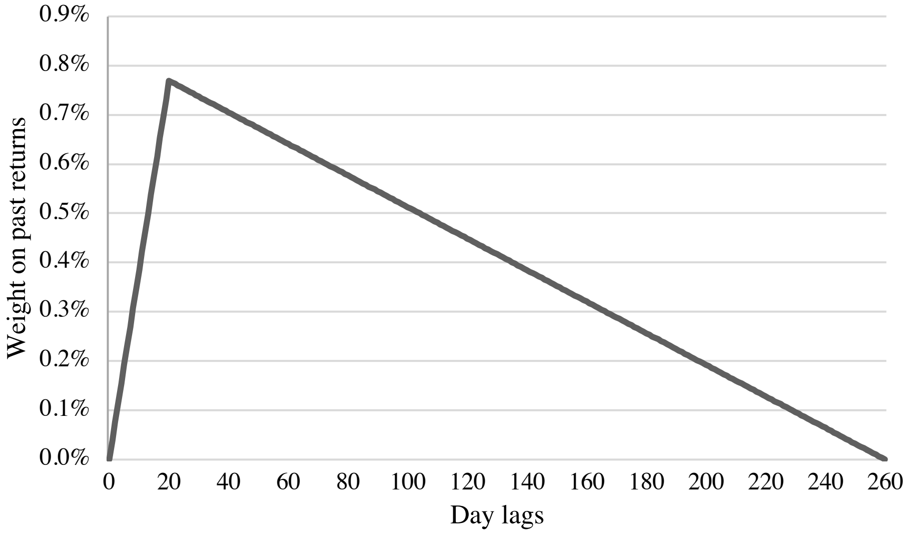
Notes: This figure illustrates how much weight a simple MACROSS assigns to past prices. MA^{fast} uses a 20-day average, and MA^{slow} uses a 260-day average. This illustration is modeled on the approach of Levine and Pedersen (2016, p. 54).

To compare MACROSS strategies with TSMOM strategies, Levine and Pedersen (2016, p. 54) altered the coefficient from dependence on past prices for a MACROSS strategy to dependence on past returns. This is because, as described in Subsection 3.2.1, the TSMOM signal is modeled on historical returns. This adjustment can be formulated in an equation with coefficients for past returns c_i as follows:

$$c_i = \sum_{i=0}^{\infty} (w_i^{fast} - w_i^{slow}) \tag{5}$$

Following this adjustment, the weighting of past returns can also be plotted in a return signature plot using Equation 5. This dependence on past returns is plotted in the following figure for the same example as described in Figure 4 and 5:

FIGURE 6: RETURN SIGNATURE PLOT OF SIMPLE MACROSS



Notes: This figure illustrates how much weight a simple MACROSS signal assigns to past returns. MA^{fast} uses a 20-day average and MA^{slow} uses a 260-day average. All weights are normalized and sum up to 1. This illustration is modeled on the approach of Levine and Pedersen (2016, p. 55).

Applying the whole methodology of this subsection to the daily return function of TSMOM (see Equation 1), the function is almost identical. Only the sign function needs to be adjusted:

$$r_{t,t+1}^{MACROSS_t^s} = sign(MACROSS_t^s) * \frac{40\%}{\sigma_t^s} * r_{t+1}^s$$

$$sign(MACROSS_t^s) \begin{cases} +1 \; if \; MACROSS_t^s > 0 \\ -1 \; if \; MACROSS_t^s < 0 \end{cases} \tag{6}$$

Based on the methodology described in this subsection, three different simple MACROSS signals were constructed. The three MA^{fast} and MA^{slow} combinations were selected to generate a short-term, medium-term, and long-term trend-following trading signal. These combinations are listed in the table below:

	MA^{fast}	**MA^{slow}**
MACROSS signal short-term	*9 days*	*60 days*
MACROSS signal medium term	*12 days*	*120 days*
MACROSS signal long-term	*5 days*	*260 days*

TABLE 3: OVERVIEW OF CONSTRUCTED SIMPLE MACROSS SIGNALS

The moving averages for the third combination were chosen because the return signature plots from the Boos and Grob (2022, p. 10) study suggest that the weighting coefficients for past futures returns resemble a simple MACROSS with similar moving averages.

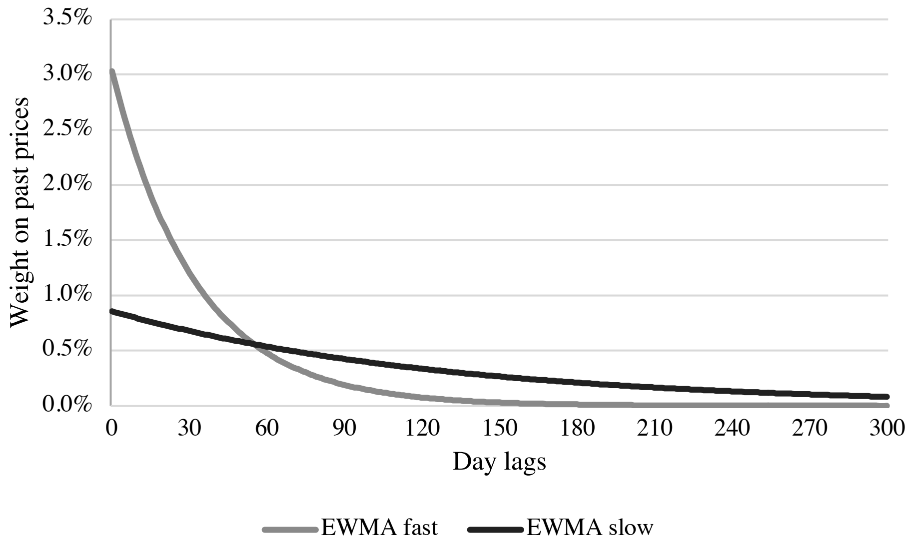
3.2.3 Exponentially Weighted Moving Average Crossover

This subsection describes the exponentially weighted MACROSS, another type of MACROSS strategy. An exponentially weighted MACROSS is similar to a simple MACROSS, but the fast and slow moving averages are exponentially, and not equally, weighted (Levine & Pedersen, 2016, p. 56). Mathematically formulated, the exponentially weighted moving averages ($\text{EWMA}^{\text{fast}}$ and $\text{EWMA}^{\text{slow}}$) are described as follows for each futures contract *s*:

$$EWMA_t^s = \frac{1}{1-\delta}\sum_{i=0}^{\infty} \delta^i P_{t-i}^s \tag{7}$$

The exponential decay factor $\delta > 0$ should be specified beforehand. Following the methodology of Levine and Pedersen (2016, p. 56), this thesis adopts a more intuitive approach by considering the COM of the moving average, defined as $\delta/(1-\delta)$, previously presented in Subsection 3.2.1 with respect to risk estimation. In an exponentially weighted MACROSS, the weights of past prices look similar to those of a simple MACROSS, but are smoother, as illustrated in Figure 7 by using an example of an $\text{EWMA}^{\text{fast}}$ with a 32-day COM and an $\text{EWMA}^{\text{slow}}$ with a 128-day COM.

FIGURE 7: PRICE SIGNATURE PLOT OF EXPONENTIALLY WEIGHTED MOVING AVERAGES



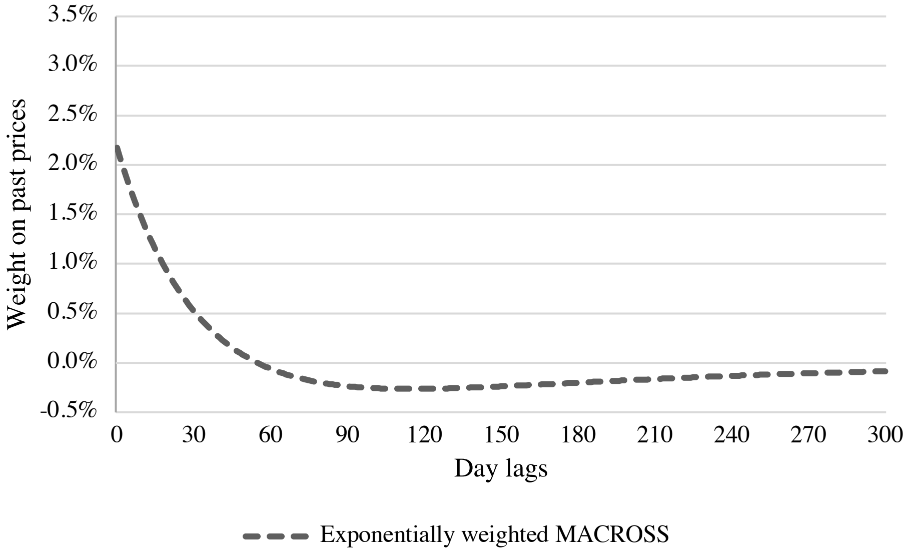
Notes: This figure illustrates how much weight an exponentially weighted moving average assigns to past prices. EWMA^{fast} is set with a 32-day COM and EWMA^{slow} with a 128-day COM. This illustration is modeled on the approach of Levine and Pedersen (2016, p. 56).

Since this strategy is also a MACROSS, the trading signal can be simplified as in Equation 4 and written as the difference between the two moving averages, in this case, EWMA$^{\text{fast}}$ and EWMA$^{\text{slow}}$:

$$MACROSS_t^s = EWMA_t^{fast,s} - EWMA_t^{slow,s} \tag{8}$$

Therefore, Equation 8 also gives a long signal when $MACROSS_t^s$ is positive and a short signal when it is negative. Thus, by using the exponentially weighted MACROSS, the weighting of recent prices is positive, but the weighting of prices further back is negative, and the weights eventually converge to zero. This weight distribution of past prices is shown below in Figure 8:

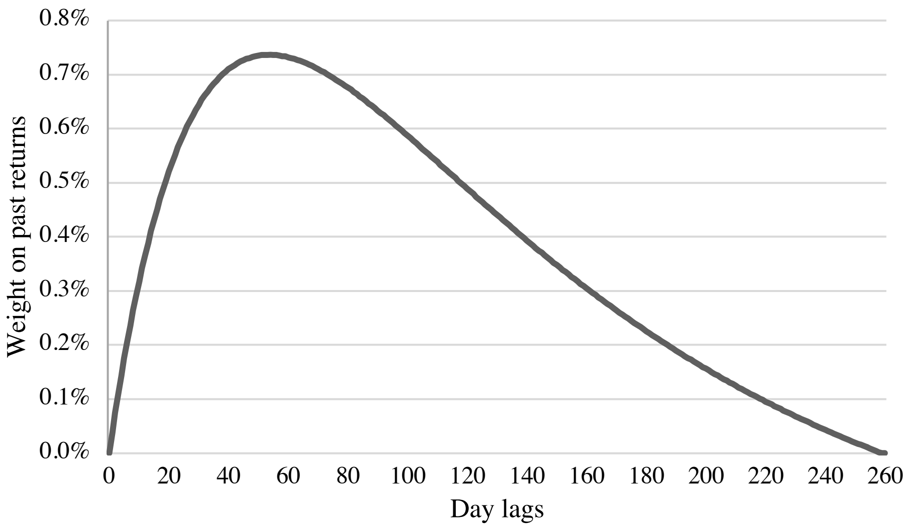
FIGURE 8: PRICE SIGNATURE PLOT OF EXPONENTIALLY WEIGHTED MACROSS



Notes: This figure illustrates how much weight an exponentially weighted MACROSS assigns to past prices. $EWMA^{fast}$ is set with a 32-day COM and $EWMA^{slow}$ with a 128-day COM. This illustration is modeled on the approach of Levine and Pedersen (2016, p. 56).

Using the same approach as in Subsection 3.2.2 to adapt the dependence on past prices to past returns, the dependency on past returns can be represented in the following return signature plot:

FIGURE 9: RETURN SIGNATURE PLOT OF EXPONENTIALLY WEIGHTED MACROSS



Notes: This figure illustrates how much weight an exponentially weighted MACROSS signal assigns to past returns. $EWMA^{fast}$ uses a 32-day COM and $EWMA^{slow}$ uses a 128-day COM. All weights are normalized and sum up to 1. This illustration is modeled on the approach of Levine and Pedersen (2016, p. 57).

The daily return function is again nearly identical to Equation 6, the only difference being the sign function, which is replaced by the signal determination from Equation 8.

In the same procedure as the two previously explained trading signals, three exponential MACROSS signals were constructed in this thesis. The three EWMA^{fast} and EWMA^{slow} combinations were selected to generate a short-term, medium-term and long-term trend-following trading signal. These combinations are shown in the table below:

	EWMA^{fast}	**EWMA^{slow}**
MACROSS signal short-term	*COM=3 days*	*COM=12 days*
MACROSS signal medium term	*COM=8 days*	*COM=32 days*
MACROSS signal long-term	*COM=32 days*	*COM=128 days*

TABLE 4: OVERVIEW OF CONSTRUCTED EXPONENTIALLY WEIGHTED MACROSS SIGNALS

These combinations of different moving averages were selected following the methodology of Levine and Pedersen (2016, p. 61), which aimed to have similar trend horizons as the three TSMOM look-back horizons described in Subsection 3.2.1.

3.2.4 Risk and Return Characteristics of Trend-Following Signals

Table 5 shows the performance of each of the trend-following strategies described previously. The strategies deliver positive results in all cases, which is a consistent result. The average Sharpe ratio (excess return divided by realized volatility) across all strategies increases for each strategy as the look-back horizon expands. When comparing the three strategies, it is noticeable that the TSMOM strategy delivers the highest performance throughout the different look-back horizons. In addition, when examining returns, it is apparent that the time horizons for all three strategy types appear to be reasonably set, as the values of the strategies are similar across the look-back periods.

The annual volatility for each strategy is consistent at around 13%. As described in Section 3.2.4, the approach of Moskowitz et al. (2012, p. 233) was followed and each position was scaled to 40% annual volatility. After this scaling, the weights of the instruments were divided equally. By diversifying the individual positions, Moskowitz et al. (2012, p. 236) obtained a strategy-wide volatility of 12%, which is one percentage point less than in our results using the same procedure. This deviation may be because not exactly the same instruments or the same time period were analyzed.

	Short-term signals	*Medium-term signals*	*Long-term signals*
	1-month TSMOM	**3-month TSMOM**	**12-month TSMOM**
Excess return	*7.63%*	*9.02%*	*11.52%*
Volatility	*13.28%*	*13.39%*	*13.18%*
Sharpe ratio	*0.57*	*0.67*	*0.87*
Annualized alpha	*14.72%**** *(3.132)*	*12.87%**** *(2.698)*	*15.61%**** *(3.276)*
	9/60 MACROSS	**12/120 MACROSS**	**5/260 MACROSS**
Excess return	*6.92%*	*9.03%*	*10.31%*
Volatility	*13.58%*	*13.62%*	*13.31%*
Sharpe ratio	*0.51*	*0.66*	*0.77*
Annualized alpha	*10.39%*** *(2.138)*	*10.77%*** *(2.189)*	*14.43%**** *(3.012)*
	3/12 COM MACROSS	**8/32 COM MACROSS**	**32/128 COM MACROSS**
Excess return	*7.00%*	*9.5%*	*10.52%*
Volatility	*13.48%*	*13.82%*	*13.50%*
Sharpe ratio	*0.52*	*0.69*	*0.78*
Annualized alpha	*13.90%**** *(2.928)*	*11.54%*** *(2.367)*	*9.88%*** *(2.067)*

TABLE 5: RISK AND RETURN CHARACTERISTICS OF TREND-FOLLOWING SIGNALS
*Notes: The statistical significance of the annualized alpha is presented at the 10%, 5% and 1% levels using the asterisks *, ** and ***. In addition, the t-statistics are presented in parentheses.*

In addition to the average annual excess return, volatility, and Sharpe ratio, Table 5 also reports the annualized alpha from the following regression:

$$\begin{aligned} r_t^{trend\ signal} &= \alpha + \beta^1 r_t^{Market} + \beta^2 r_t^{Bonds} + \beta^3 r_t^{GSCI} + \beta^4 r_t^{SMB} \\ &\quad + \beta^5 r_t^{HML} + \beta^6 r_t^{RMW} + \beta^7 r_t^{CMA} + \beta^8 r_t^{MOM} + \varepsilon_t \end{aligned} \tag{9}$$

This regression evaluates the returns of the described trend-following strategies relative to standard asset-pricing benchmarks. In this thesis, trend-following strategies were regressed on the excess returns of a passive investment in the equity market (Market), represented by the MSCI World Index minus the risk-free rate, the government bond market (Bonds), represented by the Bloomberg Global Agg Treasuries Total Return index minus the risk-free rate, and the commodity market (GSCI), represented by the S&P GSCI Commodity index.[3] In addition, the standard Fama and French (2015) and Carhart (1997) stock

[3] The daily values of these three indices are obtained from Bloomberg. The risk-free rate is derived from Kenneth R French's website.

market factors SMB, HML, RMW, CMA, and MOM for size, value, profitability, investment patterns, and cross-sectional momentum premiums were also considered.[4] Thus, alpha measures the excess return after accounting for the risk premiums associated with a long position in these traditional asset classes. In comparison to the alpha analysis of Moskowitz et al. (2012, pp. 234–235) for their TSMOM strategy, this thesis thus incorporates the five-factor model of Fama and French instead of the three-factor model, in addition to the momentum factor.

In all cases, the alphas are significantly positive and even larger than the actual excess returns. Hurst et al. (2013, p. 47) explain this by stating that TSMOM strategies are both long and short and, therefore, have a low average exposure to such passive factors. This is also applicable to the two MACROSS strategies, because as Levine and Pedersen (2016) describe theoretically and empirically, most TSMOM and MACROSS signals are largely equivalent and describe each other. In summary, the alpha results presented in Table 5 demonstrate the presence and significance of momentum for the three different trend-following strategies and are robust across the three look-back periods in each case.

Moreover, the trend following strategies considered in this thesis have performed particularly well in periods of prolonged bear markets and in prolonged bull markets, as can be seen in Figure 10. This figure plots the monthly returns of the trend following strategy against the monthly returns of the MSCI World Index. A quadratic function was then estimated to fit the relationship between trend signal returns and market returns, resulting in a "smile" curve. The estimated smile curve means that trend-following strategies have historically performed best in significant bear markets or significant bull markets, and less well in flat markets. Such a smile curve was also prominent in previous literature (Baltas & Kosowski, 2013, p. 17; Hurst et al., 2013, p. 51). Hurst et al. (2013, p. 51) attribute this occurrence to the fact that most of the worst bear markets in history did not occur immediately, but gradually. Given these performance characteristics, it is also clear that the monthly losses of the market, as shown in Figure 10, were notably more severe than those of the trend-following strategies during the period under consideration. This demonstrates that there is some sort of downside constraint in tracking trends. The lower downside risk is probably a consequence of the diversification provided by the adaptive

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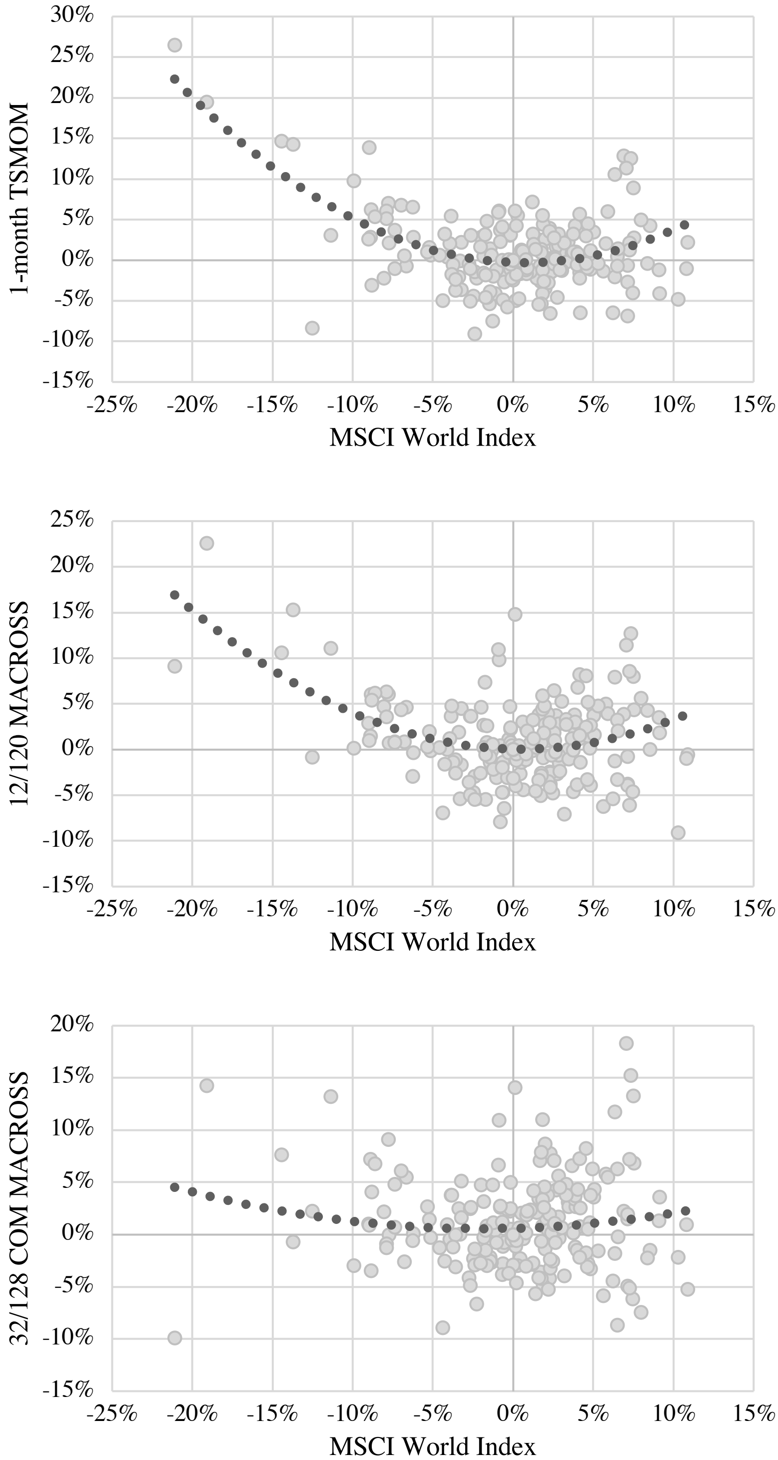
[4] The stock market factors SMB, HML, RMW, CMA and MOM were also obtained from Kenneth R French's website.

risk approach and the large number of underlying instruments as well as the daily re-balancing.

FIGURE 10: TREND-FOLLOWING AGAINST THE MARKET



Notes: These charts show the monthly excess returns of trend following strategies compared to the MSCI World Index from 1999 to 2022. The dark-gray dotted line represents a quadratic fit in each graph. One strategy from each of the three signal categories was chosen to show all look-back periods. A detailed listing of all signals is shown in Appendix B3.

3.2.4.1 Correlation of the Trend-Following Signals

Table 6 shows the correlation statistics of the trend-following strategies and the managed futures indices in this study. The correlation between the strategies is very high among the comparable time horizons. This finding is consistent with the study by Levine and Pedersen (2016), which explained the relationship between TSMOM and MACROSS strategies. The researchers demonstrated that different forms of trend-following investment strategies are equivalent and can mutually describe each other to a high degree. However, the correlations between strategies over different time horizons are relatively modest. A fundamental reason for these low correlations is that, as Hurst et al. (2013, p. 50) report, the average correlation between the underlying asset classes is rather low. This factor can lead to diversification benefits between different strategies or even within a strategy between various look-back horizons, which can be exploited by CTAs.

Furthermore, Table 6 presents the correlations between the trend-following strategies and the managed futures indices described in Section 3.1. The results of these correlation statistics seem to support the hypothesis posed at the beginning of Chapter 3 that MACROSS strategies are better able than TSMOM strategies to replicate the returns of managed futures funds. This is because the correlation values are higher among MACROSS signals for all indices. Moreover, for three of the four indices, the correlation between the simple MACROSS strategy with MA^{fast} of 5 days and MA^{slow} of 260 days is the strongest. For the other index, the HFRX Macro Systematic Diversified CTA Index (12), the medium-term simple MACROSS with MA^{fast} of 12 days and MA^{slow} of 120 days has the highest correlation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
1-month TSMOM (1)	*1.00*												
3-month TSMOM (2)	*0.59*	*1.00*											
12-month TSMOM (3)	*0.29*	*0.53*	*1.00*										
9/60 MACROSS (4)	*0.76*	*0.82*	*0.45*	*1.00*									
12/120 MACROSS (5)	*0.55*	*0.90*	*0.60*	*0.83*	*1.00*								
5/260 MACROSS (6)	*0.43*	*0.74*	*0.86*	*0.65*	*0.83*	*1.00*							
3/12 COM MACROSS (7)	*0.91*	*0.68*	*0.34*	*0.84*	*0.63*	*0.51*	*1.00*						
8/32 COM MACROSS (8)	*0.66*	*0.91*	*0.56*	*0.92*	*0.95*	*0.79*	*0.75*	*1.00*					
32/128 COM MACROSS (9)	*0.20*	*0.53*	*0.90*	*0.42*	*0.65*	*0.87*	*0.27*	*0.58*	*1.00*				
CTA-index 1 (10)	*0.17*	*0.35*	*0.40*	*0.32*	*0.41*	*0.46*	*0.22*	*0.38*	*0.43*	*1.00*			
CTA-index 2 (11)	*0.40*	*0.66*	*0.65*	*0.64*	*0.74*	*0.75*	*0.48*	*0.72*	*0.69*	*0.54*	*1.00*		
CTA-index 3 (12)	*0.21*	*0.42*	*0.37*	*0.38*	*0.47*	*0.47*	*0.27*	*0.45*	*0.41*	*0.49*	*0.58*	*1.00*	
CTA-index 4 (13)	*0.31*	*0.57*	*0.61*	*0.55*	*0.66*	*0.70*	*0.39*	*0.63*	*0.64*	*0.65*	*0.78*	*0.72*	*1.00*

TABLE 6: CORRELATION OF THE TREND-FOLLOWING SIGNALS

Notes: The CTA indices described in Section 3.1 are written in this table in the order of CTA-index 1–4.

3.3 Trend-Following Signals Explaining Managed Futures Returns

The objective of this section is to compare the explanatory power of the different trend-following signals on the performance of managed futures managers. To explain the returns of managed futures, the excess returns of managed futures indices r_t^{MF} are regressed on the returns of the short-, medium-, and long-term trend-following signals explained in the previous section:

$$
\begin{aligned}
r_t^{MF} = \alpha + \beta^1 r_t^{trend\ signal_{short-term}} + \beta^2 r_t^{trend\ signal_{medium-term}} \\
+ \beta^3 r_t^{trend\ signal_{long-term}} + \varepsilon_t
\end{aligned}
\tag{10}
$$

This regression was run for the TSMOM, the simple MACROSS, and the exponentially weighted MACROSS signals, and the results of these regressions are shown in Table 7. It is clear that the trend-following strategies explain the managed futures indices returns to a large extent, as the R^2 of these regressions are large, ranging from 0.37 to 0.72. In the analysis of the three regressions of the overarching trend-following strategy types, as already suspected, the MACROSS strategies are better able to replicate the returns of the managed futures. Furthermore, the exponentially weighted MACROSS investment signal outperforms both other strategies for all indices.

The intercepts reported in Table 7 indicate the alphas after controlling for trend-following returns. Except for the SG CTA index, all alphas of the other indices are significantly negative, which suggests that the strategies developed in this thesis outperform the returns of the managed futures indices. However, since this work does not have management and transaction fees incorporated into the strategies, this performance cannot be relied upon.

In most cases, the relevance of the signals increases with the duration of the look-back horizons. In 8 out of a total of 12 regressions, the long-term signal has the highest estimated regression coefficient, and the result is significant at the 1% level in each case. However, this is not the case for Hurst et al. (2013, p. 53), where the short-term 1-month TSMOM has the largest regression coefficient. In contrast, the short-term coefficients in Table 7 are either significant and marginally negative or positive, and in four instances, not significant at all. The small positive and slightly negative coefficients for these signals suggest that managers might tend to avoid short-term momentum strategies or add them only slightly as an overlay to their longer-term strategies.

Comparing the outcome of the regression results in Table 7 with the performance in Sub-section 3.2.4, it makes sense that the long-term signals are weighted more, as they provide a better return across all signals and look-back horizons. The difference to Hurst et al. (2013, p. 53) could be from the fact that they regress the performance of two other indices and five actual funds and only allow weekly portfolio rebalancing, whereas daily re-balancing is used in this thesis.

TSMOM	**1-month TSMOM**	**3-month TSMOM**	**12-month TSMOM**	**Intercept**	**R^2**
HFRX Macro/CTA	*-0.026**** (-4.163)	*0.130**** (19.098)	*0.189**** (32.777)	*-2.78%*** (-2.534)	*0.37*
SG CTA	*0.015*** (2.318)	*0.258**** (34.823)	*0.253*** (40.349)	*-1.81%* (-1.568)	*0.56*
HFRX Macro Systematic Diversified CTA	*-0.017** (-1.889)	*0.284**** (29.442)	*0.219*** (26.206)	*-3.36%*** (-2.147)	*0.48*
SG CTA Mutual Fund	*-0.072**** (-6.356)	*0.275**** (21.723)	*0.365**** (33.183)	*-4.96 %**** (-2.761)	*0.62*
Simple MACROSS	**9/60 MACROSS**	**12/120 MACROSS**	**5/260 MACROSS**	**Intercept**	**R^2**
HFRX Macro/CTA	*-0.013* (-1.555)	*0.068**** (5.938)	*0.229**** (26.733)	*-2.57%*** (-2.426)	*0.41*
SG CTA	*0.087**** (9.916)	*0.137**** (11.417)	*0.281**** (30.939)	*-1.30%* (-1.195)	*0.61*
HFRX Macro Systematic Diversified CTA	*0.031**** (2.736)	*0.175**** (11.284)	*0.264**** (21.612)	*-2.47%** (-1.683)	*0.54*
SG CTA Mutual Fund	*0.017* (1.191)	*0.117**** (5.952)	*0.423**** (26.167)	*-3.16%** (-1.878)	*0.67*
Exponentially weighted MACROSS	**3/12 COM MACROSS**	**8/32 COM MACROSS**	**32/128 COM MACROSS**	**Intercept**	**R^2**
HFRX Macro/CTA	*-0.013** (-1.775)	*0.128**** (14.845)	*0.208**** (34.287)	*-2.56%*** (-2.477)	*0.43*
SG CTA	*0.014** (1.857)	*0.277**** (31.012)	*0.255**** (40.181)	*-1.40%* (-1.328)	*0.63*
HFRX Macro Systematic Diversified CTA	*0.004* (0.342)	*0.267**** (22.914)	*0.263**** (29.554)	*-2.40%** (-1.690)	*0.57*
SG CTA Mutual Fund	*-0.010* (-0.838)	*0.282**** (20.204)	*0.379**** (36.525)	*-3.45%*** (-2.223)	*0.72*

TABLE 7: EXPOSURE OF TREND-FOLLOWING STRATEGIES TO MANAGED FUTURES RETURNS
*Notes: The statistical significance is presented at the 10%, 5%, and 1% levels, using the asterisks *, **, and ***. In addition, the t-statistics are presented in parentheses.*

3.3.1 Risk Approaches of Managed Futures

Another unknown component of managed futures is how they manage the risk of the various exposures. In the literature, the exponentially weighted lagged squared daily return is often used to calculate ex ante volatility, and this volatility is then sized to a certain number, e.g., 40% per asset, which is described in more detail in Subsection 3.2.1, Equation 2 (Moskowitz et al., 2012; Hurst et al., 2013; Levine & Pedersen, 2016). This approach was also used to calculate the results of the previously explained trading signals. However, to get an accurate understanding of the risk management of managed futures, different risk approaches are examined in this thesis.

Gmuer and Malamud (2013, p. 2) state that despite the extensive academic research on modeling and forecasting volatility, financial professionals are reluctant to adopt new tools in this regard. In fact, they say, approaches based on exponentially weighted moving averages are still widely used in the financial sector, both to estimate and predict volatility. Since this thesis is about the replication of returns that occur in practice, it maintains the same approach. However, instead of using one parameter to define the relative weights of the exponentially weighted moving average model, several parameters have been analyzed in this thesis. In the research approach of Moskowitz et al. (2012, p. 233), which was then adopted in further studies, this decay parameter (δ) was determined such that the COM results in 60 days ($\frac{\delta}{1-\delta} = 60$). In order to get a more precise overview of the explanatory power of the managed futures returns, the parameters that the COM equals, that is, 5 days, 10 days, 20 days, 60 days, and 260 days, have now been examined. Using these parameters, the daily returns of the trend-following signals were calculated again and similar to Equation 10 subjected to a regression against the excess returns of the managed futures indices. The R^2 values of the regressions based on each risk parameter are presented below:

	COM 5 days	**COM 10 days**	**COM 20 days**	**COM 60 days**	**COM 260 days**
HFRX Macro/CTA	*0.376*	***<u>0.381</u>***	*0.380*	*0.365*	*0.315*
SG CTA	*0.645*	*0.655*	***<u>0.658</u>***	*0.641*	*0.575*
HFRX Macro Systematic Diversified CTA	*0.487*	*0.492*	***<u>0.493</u>***	*0.478*	*0.428*
SG CTA Mutual Fund	*0.620*	*0.630*	***<u>0.634</u>***	*0.624*	*0.578*

TABLE 8: EXPOSURE TO MANAGED FUTURES RETURNS BASED ON DIFFERENT RISK PARAMETERS
Notes: The R^2 values in bold and underlined formatting represent the highest score of all regressions of the respective index.

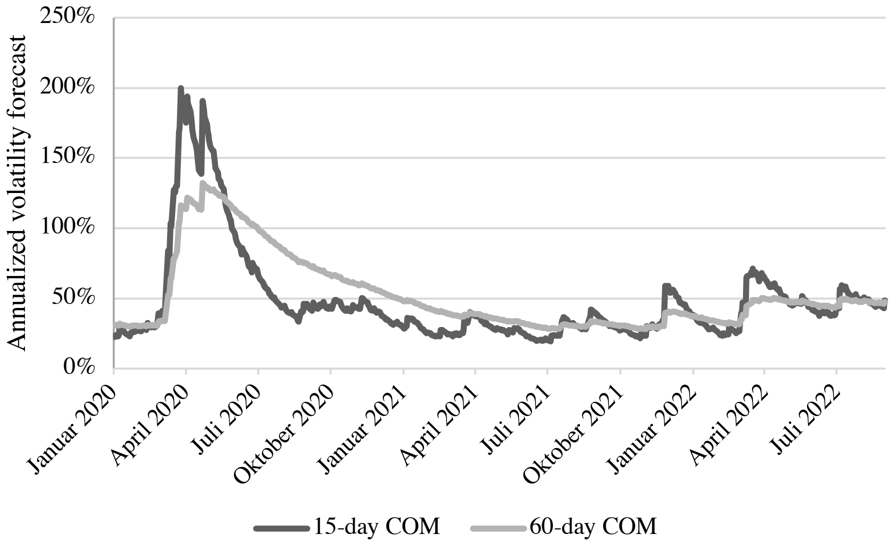
The results presented in Table 8 indicate that a decay parameter at which the COM equals 60 days is not optimal for replicating the returns of managed futures funds. Moreover, the results imply that a lower decay parameter has a better explanatory power. From this finding, it can be deduced that in practice, volatility is calculated and projected from exponential moving averages, but with a lower decay parameter than that used in previous literature on trend-following signals. Considering the results of Table 8 in more detail, a decay parameter between the 10-day or 20-day COM, in conjunction with the trend-following signals, seems to describe the returns of the managed futures most accurately. For this reason, annualized volatility is henceforth calculated in this thesis using exponentially weighted average returns (see Equation 2) with a decay parameter of a 15-day COM. Solving the COM equation to obtain the exact decay parameter results in a rounded value of 0.94 for a 15-day COM. This is demonstrated by the following calculation:

$$\sum_{i=0}^{\infty}(1-\delta)\delta^i i = \delta/(1-\delta) = 15$$
$$\delta = 0.9375 \tag{11}$$

This observation reveals considerable similarities with the prevalent *RiskMetrics* approach to estimating volatility developed by J.P. Morgan (1996). RiskMetrics introduced the exponentially weighted moving average model to forecast volatilities and correlations of a multivariate normal distribution. This approach has two important advantages over an equally weighted model (J.P. Morgan, 1996, p. 78). The first is that volatility forecasts respond more quickly to shocks in the market because recent data carry more weight than data from the distant past. Second, volatility decreases exponentially after a market shock as the weight of the shock observation diminishes. J.P. Morgan (1996, p. 100) proposes to set the decay factor for a daily data set at 0.94 and the decay factor for monthly data at 0.97. This calculation provides a possible explanation for the 60-day COM being used in the Moskowitz et al. (2012) study. They used only monthly data, and a 60-day COM is more akin to a decay parameter of 0.97.

Finally, the use of a 15-day COM as a decay parameter is advantageous in this thesis not only because exclusively daily data are evaluated, but also because a lower decay parameter is more responsive to recent data. Although higher decay factors lead to more stable predictions because they remove noise from more recent data, this procedure does not necessarily equate to more accurate predictions. This is graphically illustrated in the figure below, using the Gasoline futures contract as an example for the calculation of ex ante volatility:

FIGURE 11: VOLATILITY FORECAST OF GASOLINE FUTURE WITH DIFFERENT DECAY PARAMETERS



Notes: The data set was limited in time from January 1, 2020, to August 31, 2022, for a more substantial representation of the differences between the two decay parameters.

In summary, from this analysis on the risk methods of managed futures, it can be said that with a substantial probability, the RiskMetrics approach is still widespread and is used by CTAs.

3.3.2 Properties of the Exposure to Various Assets

To get a more detailed overview of the investment behavior of CTAs, this subsection examines the exposure associated with the individual instruments. In order to analyze this, the returns of the managed futures indices are regressed on the trend-following returns of the respective futures and currency pairs. In order to avoid doing a regression for each signal with the 67 instruments analyzed in this thesis, this part is narrowed down to a single signal. This signal is determined from a previous regression, where the returns of the indices are regressed on the returns of all nine signal variations described in Section 3.2. The results of this regression are displayed in Table 9. The characteristic of this signal should be to have the highest exposure to all four indices.

		Managed futures indices			
		(1)	**(2)**	**(3)**	**(4)**
	Annualized alpha	*-2.39***	*-1.26%*	*-2.2%*	*-3.60%***
		(-2.318)	*(-1.206)*	*-1.560*	*-2.370*
TSMOM	**1-month TSMOM**	*-0.041****	*-0.053****	*-0.019*	*-0.045***
		(-3.538)	*(-4.459)*	*-1.183*	*-2.513*
	3-month TSMOM	*-0.037****	*-0.019*	*0.020*	*-0.018*
		(-3.162)	*(-1.571)*	*1.212*	*-0.971*
	12-month TSMOM	*-0.037****	*-0.009*	*-0.074****	*0.067****
		(-3.006)	*(-0.715)*	*-4.593*	*3.716*
Simple MACROSS	**9/60 MACROSS**	*0.054****	*0.132****	*0.090****	*0.137****
		(3.389)	*(8.061)*	*4.260*	*5.781*
	12/120 MACROSS	*0.075****	*0.125****	*0.113****	*0.187****
		(3.754)	*(6.090)*	*4.014*	*6.339*
	5/260 MACROSS	*0.060****	*0.029**	*0.054***	*0.077****
		(3.755)	*(1.701)*	*2.488*	*3.077*
Exponentially weighted MACROSS	**3/12 COM MACROSS**	*0.021*	*0.041****	*0.019*	*-0.001*
		(1.495)	*(2.761)*	*0.968*	*-0.052*
	8/32 COM MACROSS	*0.019*	*0.059***	*0.042*	*-0.020*
		(0.707)	*(2.147)*	*1.126*	*-0.497*
	32/128 COM MACROSS	*0.199****	*0.242****	*0.292****	*0.265****
		(13.993)	*(16.418)*	*15.554*	*13.625*
	R^2	*0.44*	*0.64*	*0.58*	*0.73*

TABLE 9: EXPOSURE OF COMBINED TREND-FOLLOWING STRATEGIES TO MANAGED FUTURES RETURNS
*Notes: The statistical significance is presented at the 10%, 5%, and 1% levels using the asterisks *, **, and ***. The t-statistics are presented in the parentheses.*

The regression results, which are presented in Table 9, show the different exposures of the managed futures indices to the trend signals analyzed in this thesis. These results reveal that the long-term exponentially weighted MACROSS strategy indeed has by far the largest exposure to the indices. Also, this result is statistically significant at the 1% level for all four regressions. However, because of the high correlation between individual signals described in Subsection 3.2.4.1 and because all the signals are tested together in this regression, precautions could be taken to check for multicollinearity. The greater the multicollinearity, the less reliable the estimates of the regression (Alin, 2010, p. 370). Since the focus in this section is not on this regression per se, no further analysis on multicollinearity or corrective measures is conducted here. It can be concluded that in order to assess the exposure of the individual instruments to CTAs, it is reasonable to regress the returns of the managed futures indices on the individual asset returns derived only from the long-term exponentially weighted MACROSS signal. Besides, the differences between the returns of the strategies with a high correlation (see Subsection 3.2.4.1) would most likely not be substantial.

As a next step, the returns of the indices were regressed on the returns of the long-term exponentially weighted MACROSS strategy of all individual instruments. The objective of this regression was to measure the weighting of the individual assets on the returns of the indices. However, to provide an overview, only the five highest coefficients are summarized in this thesis according to the asset classes commodities, equities, bonds, and currency pairs. To get a meaningful overview of the validity of these weighting coefficients, they are compared with the average daily trading volume of the trailing twelve months (TTM) in Figure 12 and with the Sharpe ratio in Figure 13. The trading volume for the currencies is missing in Figure 12 because the Bloomberg Total Carry Return Index was used as the data set there. However, the selected currency pairs correspond to the most traded currencies (G10 currencies). The results for these asset classes are discussed below.

3.3.2.1 Exposure to Commodities

According to the regression results, returns of gold futures have the largest impact on managed futures returns, suggesting that the largest exposure of managed futures funds to the commodity class is gold futures. In the subsequent ranks, it does not look so clear. However, the energy futures seem to dominate afterwards slightly, with WTI and gasoline futures representing one of the five highest weighting coefficients for all four indices. In addition, heating oil futures have the third-highest weighting coefficient for the third index return.

3.3.2.2 Exposure to Equities

The estimated weighting coefficients of equity index futures indicate that CTAs tend to invest in Asian equity markets, as Asian index futures are represented in the upper five of all managed futures indices analyzed. One reason for this could be that some CTAs believe that trends are more prevalent and pronounced in Asia. Monsoon Capital, for example, is a CTA that trades exclusively in Asian equity markets because the fund manager believes they are driven more by retail investor emotions than US or European equity markets (Melin, 2014, p. 149).

3.3.2.3 Exposure to Bonds

In terms of bond futures exposure, managed futures appear to be diversified across European and U.S. government bond futures. These two regions represent the five largest influencing factors for all the managed futures indices analyzed.

3.3.2.4 Exposure to Currencies

For the currencies, the impact is not distinct. However, the currency pairs JPY/USD, AUD/USD, and CHF/USD represent one of the five highest influencing factors on the returns for all indices examined.

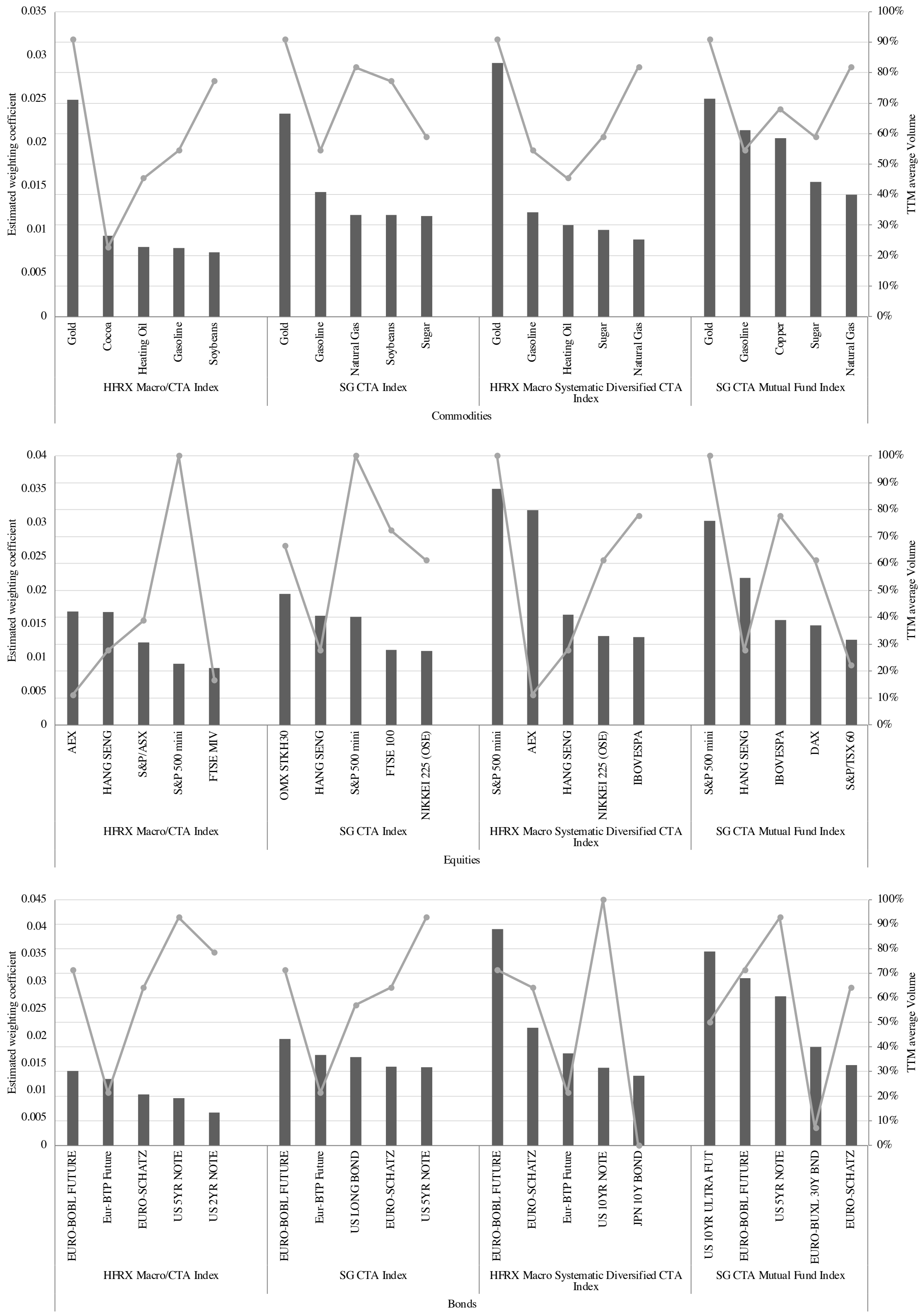
3.3.2.5 Overall Exposure Compared to Trading Volume

The average daily trading volume over the last 12 months was measured in Figure 12 for the respective determinants according to their percentiles in the asset class. Comparing these results across all asset classes, it is not obvious whether trading volume plays a decisive role for the CTAs for these assets. While there are many of the most traded instruments in each class, they are grouped together with some of the comparably less traded assets. However, it should be noted that all assets are already liquid futures contracts. The average daily trading volume for these assets over the past year is shown in Appendix A, Table A1.

3.3.2.6 Overall Exposure Compared to Sharpe Ratio

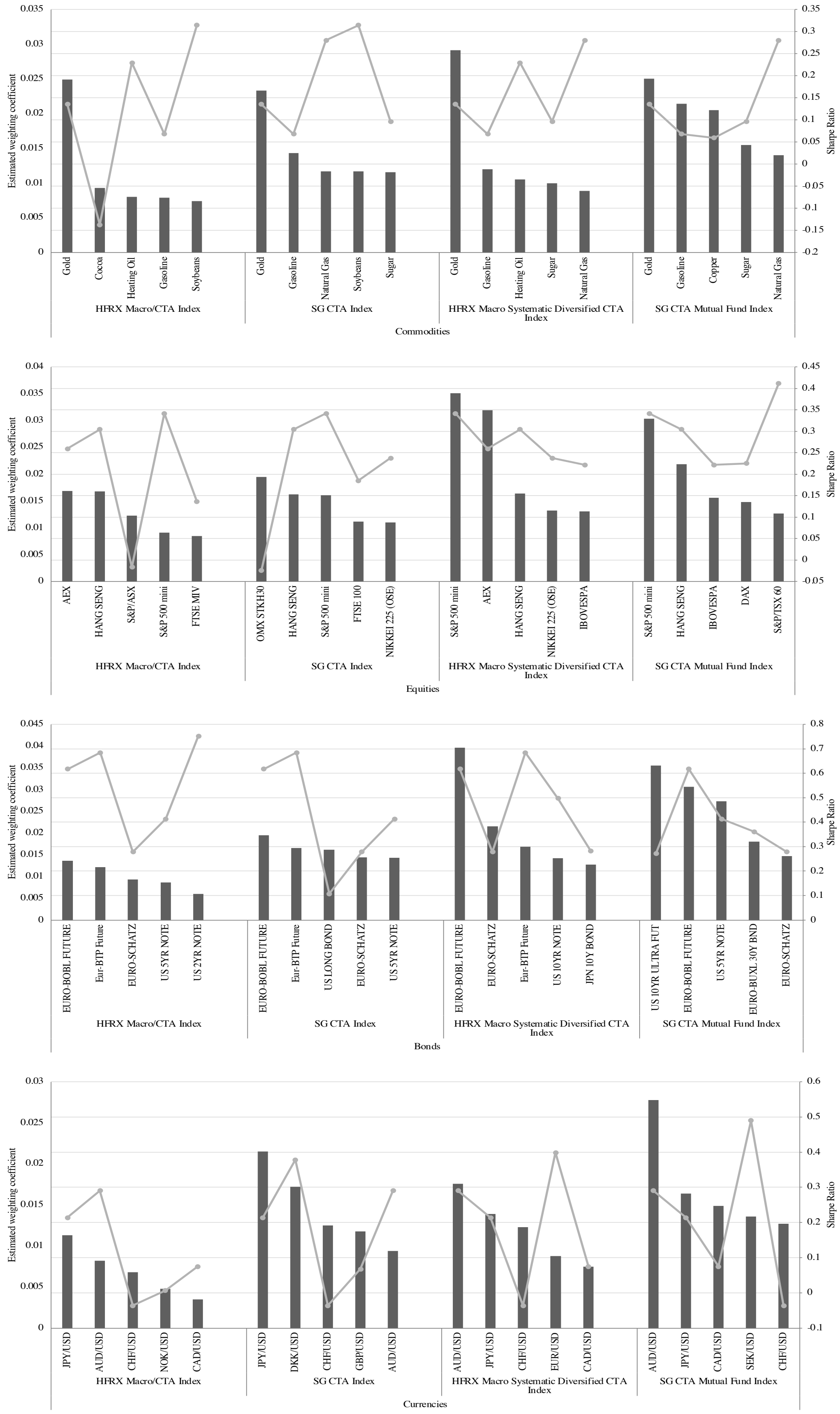
By comparing the highest regression coefficients with the respective Sharpe ratio of the according instrument in Figure 13, no clear pattern is visible. It appears that CTAs do not base their investments on individual instruments and the associated expected returns. The most likely reason is that they are more oriented towards the complete portfolio because of the diversification benefits between the individual asset returns as mentioned in Subsection 3.2.4.1.

FIGURE 12: WEIGHTING COEFFICIENTS OF THE INDIVIDUAL ASSETS COMPARED TO TRADING VOLUME



Notes: The dark-gray bars represent the weighting coefficient estimated by regression and are scaled on the left axis. All these coefficients are statistically significant, and the full regression statistics are presented in Appendix C. The light-gray lines represent the average daily TTM trading volume of each asset and are plotted based on the percentile of each asset category.

FIGURE 13: WEIGHTING COEFFICIENTS OF THE INDIVIDUAL ASSETS COMPARED TO SHARPE RATIO



Notes: The dark-gray bars represent the weighting coefficient estimated by regression and are scaled on the left axis. All these coefficients are statistically significant, and the full regression statistics are presented in Appendix C. The light-gray lines represent the Sharpe ratio of each asset and are plotted on the right axis scale.

3.3.3 Long and Short Sides of Trend-Following

Brock et al. (1992, p. 1734), who examined simple technical trading rules (including MACROSS), demonstrated that the long side of technical trading rules is more profitable than the short side. Furthermore, Agerback, Gudmundsen-Sinclair, and Peltomäki (2019) also demonstrated that the long and short sides of trend followers are not uniform by exploring whether trend followers might overweight their exposure to the long or short side of a trend effect because some investors were less willing or able to take short positions in certain markets.

The results of Agerback et al. (2019, p. 70) show that the long side is significantly more profitable for stocks, bonds, and commodities. It is noteworthy, however, that this result does not hold for foreign exchange, where profitability does not appear to be significantly different between the long and short sides with respect to U.S. dollar positions. This divergent result for foreign exchange may be related to the fact that currency positions are not inherently long or short (Agerback et al., 2019, p. 70). Moreover, Cont (2001, p. 224) lists gain/loss asymmetry, meaning larger drawdowns than upside swings, as a stylized statistical property of asset returns, but explicitly points out that this result does not hold for exchange rates. This asymmetry can be observed, for example, for the MSCI World Index in Figure 10.

3.3.3.1 Risk and Return Characteristics of Long or Short Trend-Following Signals

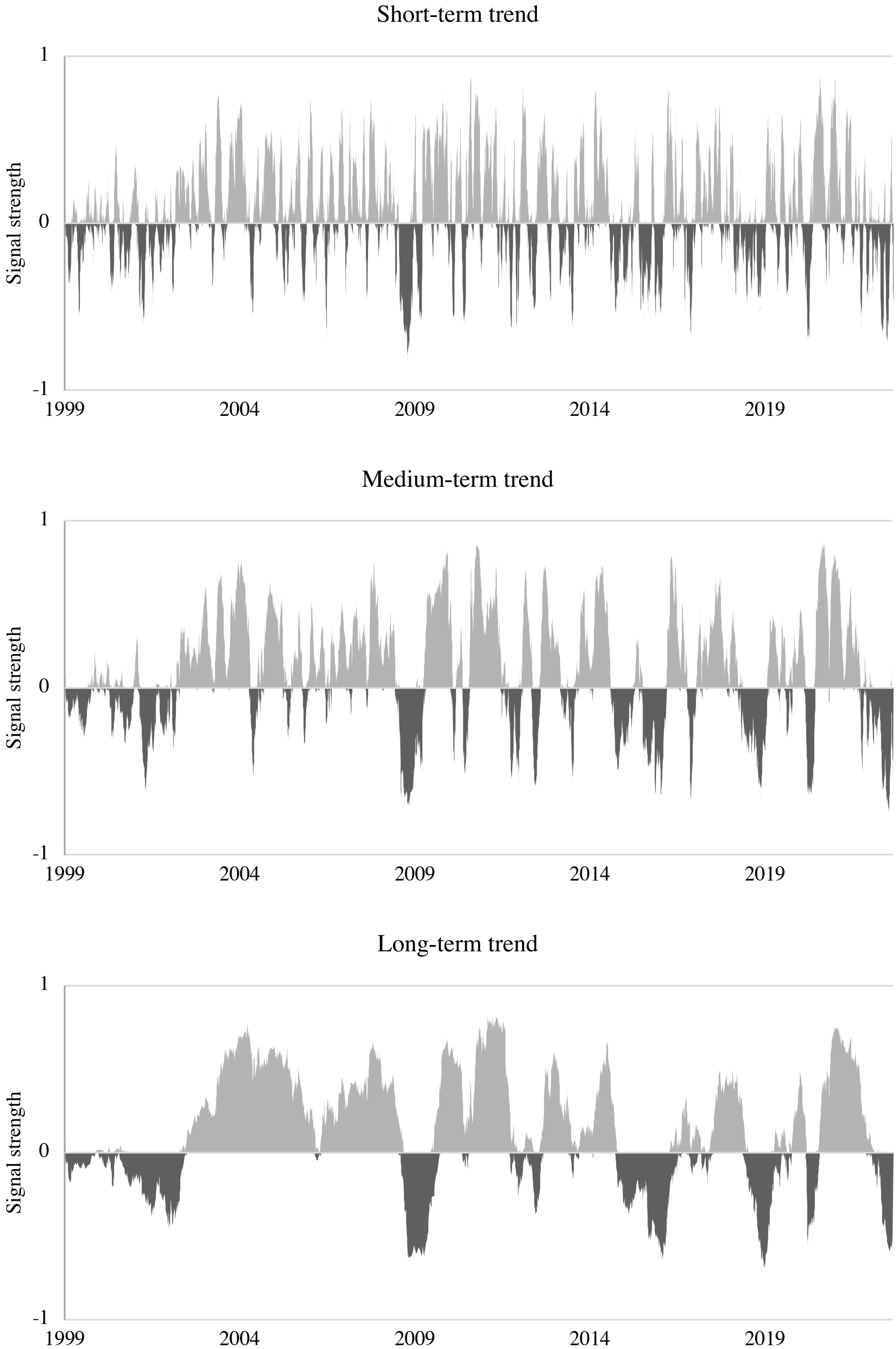
While Agerback et al. (2019, pp. 66–68) restricted combined trend-following strategies to invest only long or short and separated them by asset classes, in this thesis, the trend-following signals described in Section 3.2 are divided into long- and short-only and compared. The results, shown in Table 10, are in line with the literature. As discussed, the risk-weighted returns are more profitable for the long signals than for the short signals. In fact, the returns of the short- and medium-term short-only signals are negative. There is also no obvious difference between the three overarching signal types. In addition, Table 10 also reports the annualized alpha from the regression described in Equation 9. In all but two cases, the alphas are significantly positive. Only the simple short- and medium-term MACROSS short-only signals do not significantly outperform the broad risk factors. However, a sharp drop-off is also observed between the alphas of the long and short sides. This finding suggests that the long- or short-only trend-following strategies have a low average exposure to these passive factors, but this is more the case for the symmetric trend-following strategies. The symmetric trend-following signals have substantially higher alphas (see Table 5).

	Short-term signals		*Medium-term signals*		*Long-term signals*	
	1-month TSMOM		**3-month TSMOM**		**12-month TSMOM**	
Excess return	*9.27%*	*-1.08%*	*10.20%*	*-0.27%*	*11.14%*	*0.88%*
Volatility	*10.65%*	*10.93%*	*11.15%*	*10.47%*	*11.57%*	*9.85%*
Sharpe ratio	*0.87*	*-0.10*	*0.92*	*-0.03*	*0.96*	*0.09*
Annualized alpha	*9.07%****	*5.99%***	*8.28%***	*5.23%**	*9.71%****	*6.79%****
	(2.878)	*(2.111)*	*(2.483)*	*(1.942)*	*(2.847)*	*(2.606)*
	9/60 MACROSS		**12/120 MACROSS**		**5/260 MACROSS**	
Excess return	*9.04%*	*-1.48%*	*10.2%*	*-0.48%*	*10.58%*	*0.33%*
Volatility	*11.18%*	*10.59%*	*11.48%*	*10.28%*	*11.54%*	*9.88%*
Sharpe ratio	*0.81*	*-0.14*	*0.89*	*-0.05*	*0.92*	*0.03*
Annualized alpha	*7.06%***	*4.01%*	*7.13%***	*4.1%*	*8.88%****	*5.95%***
	(2.113)	*(1.445)*	*(2.068)*	*(1.517)*	*(2.584)*	*(2.317)*
	3/12 COM MACROSS		**8/32 COM MACROSS**		**32/128 COM MACROSS**	
Excess return	*8.69%*	*-1.69%*	*9.94%*	*-0.44%*	*10.45%*	*0.07%*
Volatility	*10.87%*	*10.88%*	*11.45%*	*10.49%*	*11.97%*	*9.68%*
Sharpe ratio	*0.80*	*-0.16*	*0.87*	*-0.04*	*0.87*	*0.01*
Annualized alpha	*8.90%****	*5.76%***	*7.60%***	*4.46%**	*7.01%***	*3.86%*
	(2.767)	*(2.052)*	*(2.222)*	*(1.652)*	*(2.025)*	*(1.524)*

TABLE 10: RISK AND RETURN CHARACTERISTICS OF LONG AND SHORT TREND-FOLLOWING SIGNALS
*Notes: The values that have a gray background are related to the short-only signals. The statistical significance of the annualized alpha is presented at the 10%, 5%, and 1% levels using the asterisks *, **, and ***. The t-statistics are presented in the parentheses.*

Comparing the risk and return of these asymmetric signals with the performance of the symmetric trend signals, the results of which are shown in Table 5, reveals that the long-only signals perform better than the symmetric signals, as measured by the Sharpe ratio. This could be because markets have been exhibiting upwards trends over the last decades. Figure 14 illustrates that all trend signals averaged over each look-back horizon have more buy signals than sell signals over the time period examined. This effect increases with the extension of the look-back horizon, which means that especially long-term trends have signaled buy strategies in the last decades.

FIGURE 14: SIGNAL STRENGTH ACROSS LOOK-BACK PERIODS



Notes: A positive signal indicates that all signals averaged over the specific look-back horizon have indicated a buy signal and vice versa. The periods in which, on average, a buy signal was forecasted are shown in light-gray in these figures, while the sell signals are shown in dark-gray.

3.3.3.2 Correlation of the Long and Short Trend-Following Signals

Table 11 reports the correlation statistics for the variables examined in this subsection. These variables include the long- and short-only signals, the passive investment factors discussed, and the managed futures indices. In illustrating the correlations among the trend-following signals, the pattern is the same as described earlier in Subsection 3.2.4.1. The correlation between the asymmetric signals with similar look-back horizons is strong, with values above 0.9. Between the long- and short-only returns, the correlation is, as expected, negative, and it decreases further with the larger difference of the trend horizons considered.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)	(22)	(23)	(24)	(25)	(26)	(27)	(28)	(29)	(30)
1-month TSMOM (1)	*1.00*																													
3-month TSMOM (2)	*0.84*	*1.00*																												
12-month TSMOM (3)	*0.74*	*0.82*	*1.00*																											
1-month TSMOM (4)	*-0.24*	*-0.42*	*-0.54*	*1.00*																										
3-month TSMOM (5)	*-0.37*	*-0.23*	*-0.45*	*0.83*	*1.00*																									
12-month TSMOM (6)	*-0.45*	*-0.39*	*-0.22*	*0.69*	*0.77*	*1.00*																								
9/60 MACROSS (7)	*0.91*	*0.93*	*0.79*	*-0.35*	*-0.30*	*-0.41*	*1.00*																							
12/120 MACROSS (8)	*0.83*	*0.96*	*0.85*	*-0.43*	*-0.27*	*-0.37*	*0.93*	*1.00*																						
5/260 MACROSS (9)	*0.79*	*0.90*	*0.95*	*-0.49*	*-0.36*	*-0.28*	*0.87*	*0.93*	*1.00*																					
9/60 MACROSS (10)	*-0.30*	*-0.30*	*-0.46*	*0.90*	*0.92*	*0.74*	*-0.21*	*-0.30*	*-0.39*	*1.00*																				
12/120 MACROSS (11)	*-0.36*	*-0.24*	*-0.39*	*0.81*	*0.95*	*0.79*	*-0.26*	*-0.20*	*-0.30*	*0.92*	*1.00*																			
5/260 MACROSS (12)	*-0.39*	*-0.30*	*-0.28*	*0.75*	*0.87*	*0.93*	*-0.33*	*-0.27*	*-0.22*	*0.83*	*0.91*	*1.00*																		
3/12 COM MACROSS (13)	*0.96*	*0.87*	*0.76*	*-0.28*	*-0.33*	*-0.43*	*0.94*	*0.86*	*0.82*	*-0.26*	*-0.32*	*-0.36*	*1.00*																	
8/32 COM MACROSS (14)	*0.87*	*0.96*	*0.83*	*-0.39*	*-0.27*	*-0.37*	*0.97*	*0.98*	*0.91*	*-0.26*	*-0.22*	*-0.28*	*0.91*	*1.00*																
32/128 COM MACROSS (15)	*0.73*	*0.84*	*0.96*	*-0.58*	*-0.45*	*-0.28*	*0.80*	*0.87*	*0.96*	*-0.49*	*-0.39*	*-0.29*	*0.75*	*0.86*	*1.00*															
3/12 COM MACROSS (16)	*-0.26*	*-0.38*	*-0.51*	*0.96*	*0.87*	*0.71*	*-0.30*	*-0.39*	*-0.45*	*0.93*	*0.84*	*0.78*	*-0.23*	*-0.35*	*-0.56*	*1.00*														
8/32 COM MACROSS (17)	*-0.32*	*-0.25*	*-0.41*	*0.86*	*0.95*	*0.78*	*-0.23*	*-0.23*	*-0.32*	*0.96*	*0.97*	*0.89*	*-0.29*	*-0.21*	*-0.42*	*0.90*	*1.00*													
32/128 COM MACROSS (18)	*-0.47*	*-0.37*	*-0.24*	*0.68*	*0.79*	*0.94*	*-0.40*	*-0.33*	*-0.24*	*0.74*	*0.83*	*0.93*	*-0.45*	*-0.35*	*-0.24*	*0.70*	*0.81*	*1.00*												
Market (19)	*0.31*	*0.30*	*0.32*	*-0.58*	*-0.59*	*-0.59*	*0.31*	*0.31*	*0.31*	*-0.58*	*-0.58*	*-0.60*	*0.30*	*0.31*	*0.36*	*-0.59*	*-0.59*	*-0.56*	*1.00*											
GSCI (20)	*0.36*	*0.38*	*0.37*	*-0.46*	*-0.45*	*-0.45*	*0.37*	*0.38*	*0.37*	*-0.45*	*-0.44*	*-0.46*	*0.37*	*0.37*	*0.39*	*-0.45*	*-0.45*	*-0.45*	*0.33*	*1.00*										
Bonds (21)	*0.47*	*0.45*	*0.47*	*-0.29*	*-0.30*	*-0.27*	*0.45*	*0.44*	*0.46*	*-0.30*	*-0.30*	*-0.28*	*0.46*	*0.45*	*0.46*	*-0.30*	*-0.30*	*-0.28*	*0.00*	*0.04*	*1.00*									
SMB (22)	*0.11*	*0.13*	*0.12*	*-0.06*	*-0.04*	*-0.06*	*0.12*	*0.13*	*0.12*	*-0.05*	*-0.05*	*-0.05*	*0.12*	*0.12*	*0.11*	*-0.05*	*-0.04*	*-0.05*	*0.07*	*0.10*	*-0.01*	*1.00*								
HML (23)	*0.04*	*0.05*	*0.01*	*-0.04*	*-0.04*	*-0.10*	*0.05*	*0.04*	*0.02*	*-0.04*	*-0.05*	*-0.08*	*0.05*	*0.04*	*0.00*	*-0.03*	*-0.04*	*-0.09*	*0.07*	*0.16*	*-0.07*	*0.15*	*1.00*							
RMW (24)	*-0.07*	*-0.05*	*-0.06*	*0.14*	*0.15*	*0.14*	*-0.06*	*-0.06*	*-0.05*	*0.15*	*0.15*	*0.15*	*-0.06*	*-0.06*	*-0.07*	*0.14*	*0.15*	*0.14*	*-0.30*	*-0.07*	*0.07*	*-0.27*	*0.17*	*1.00*						
CMA (25)	*0.00*	*0.02*	*0.02*	*0.08*	*0.10*	*0.10*	*0.02*	*0.03*	*0.04*	*0.09*	*0.11*	*0.11*	*0.01*	*0.03*	*0.00*	*0.09*	*0.11*	*0.10*	*-0.22*	*0.00*	*0.01*	*0.06*	*0.51*	*0.30*	*1.00*					
MOM (26)	*-0.01*	*0.00*	*-0.01*	*-0.02*	*-0.01*	*-0.02*	*0.00*	*0.00*	*-0.01*	*-0.01*	*-0.01*	*-0.02*	*-0.01*	*0.00*	*0.00*	*-0.02*	*-0.02*	*-0.02*	*0.00*	*0.01*	*0.00*	*0.00*	*0.01*	*0.00*	*0.00*	*1.00*				
CTA-index 1 (27)	*0.28*	*0.37*	*0.38*	*-0.04*	*0.07*	*0.10*	*0.36*	*0.40*	*0.42*	*0.05*	*0.11*	*0.14*	*0.31*	*0.39*	*0.39*	*-0.02*	*0.09*	*0.12*	*0.08*	*0.10*	*0.10*	*0.04*	*-0.04*	*0.00*	*0.01*	*-0.01*	*1.00*			
CTA-index 2 (28)	*0.43*	*0.57*	*0.53*	*0.09*	*0.26*	*0.26*	*0.56*	*0.61*	*0.60*	*0.25*	*0.32*	*0.33*	*0.48*	*0.61*	*0.54*	*0.14*	*0.31*	*0.29*	*-0.04*	*0.11*	*0.15*	*0.07*	*0.01*	*0.04*	*0.10*	*-0.01*	*0.54*	*1.00*		
CTA-index 3 (29)	*0.19*	*0.31*	*0.26*	*0.08*	*0.22*	*0.19*	*0.29*	*0.34*	*0.33*	*0.20*	*0.26*	*0.26*	*0.23*	*0.33*	*0.28*	*0.12*	*0.25*	*0.23*	*-0.05*	*0.00*	*0.03*	*0.00*	*-0.04*	*0.01*	*0.02*	*0.00*	*0.49*	*0.58*	*1.00*	
CTA-index 4 (30)	*0.14*	*0.28*	*0.30*	*0.23*	*0.39*	*0.41*	*0.27*	*0.33*	*0.35*	*0.37*	*0.45*	*0.47*	*0.19*	*0.32*	*0.30*	*0.28*	*0.43*	*0.45*	*-0.08*	*-0.20*	*0.00*	*-0.03*	*-0.16*	*-0.04*	*0.00*	*0.00*	*0.65*	*0.78*	*0.72*	*1.00*

TABLE 11: CORRELATION OF LONG- AND SHORT-ONLY TREND-FOLLOWING SIGNALS

Notes: The values that have a gray background are related to the short only signals. The CTA indices described in Section 3.1, are written in this table in the order of CTA-index 1-4.

3.3.3.3 Long and Short Trend-Following Signals Explaining Managed Futures Returns

Similar to the work of Agerback et al. (2019, pp. 72–75), this thesis tests the attribution of asymmetric trend-following strategies to the performance of CTAs. Those researchers also used managed futures indices as proxies for CTAs' returns. For this thesis, an important result of their work is that the long and short strategies explain CTAs' returns better than the symmetric, undivided strategies, showing that it is important to distinguish between long and short positions when explaining trend-following returns. Following this approach, this thesis also regressed the returns of managed futures indices on the long-only and short-only strategies discussed above. The regression results are presented in Table 12.

The results show the different exposures of the managed futures indices to the trend signals analyzed in this subsection. They reveal that by distinguishing between long- and short-only signals and adding the passive risk factors, the explanatory power of managed futures returns increases significantly. The R^2 values are larger for all four indices than in the previous regressions in Section 3.3. However, it should also be noted that in this regression, the improved risk approach elaborated in Subsection 3.3.1 was used, which further strengthens the replication of managed futures returns. However, because of the high correlation between the variables described in Subsection 3.3.3.2, and since all variables are tested together in this regression, precautions could be taken to check for multicollinearity. As mentioned earlier (see Subsection 3.3.2), the greater the multicollinearity, the less reliable the regression estimates. Since the estimation of the regression coefficients is crucial to answering the research question posed in the introduction, this problem is further addressed in the next section, where the most reliable and accurate signals from this regression that explain managed futures returns are selected.

		Managed futures indices			
		(1)	(2)	(3)	(4)
	Annualized alpha	*-3.35%***	*-2.97%**	*-5.36%***	*-4.86%**
		(-1.997)	*(-1.744)*	*(-2.202)*	*(-1.901)*
TSMOM	**1-month TSMOM**	*0.041*	*-0.649***	*-0.667*	*0.915**
		(0.138)	*(-2.197)*	*(-1.501)*	*(1.745)*
	3-month TSMOM	*-0.085*	*0.331*	*0.257*	*-0.354*
		(-0.172)	*(0.673)*	*(0.369)*	*(-0.500)*
	12-month TSMOM	*1.233*	*-0.605*	*3.765***	*-2.105*
		(1.161)	*(-0.589)*	*(2.424)*	*(-0.989)*
	1-month TSMOM	*-0.075*	*0.602***	*0.639*	*-0.971**
		(-0.251)	*(2.034)*	*(1.436)*	*(-1.856)*
	3-month TSMOM	*0.083*	*-0.291*	*-0.186*	*0.365*
		(0.167)	*(-0.591)*	*(-0.267)*	*(0.516)*
	12-month TSMOM	*-1.234*	*0.680*	*-3.842***	*2.288*
		(-1.162)	*(0.662)*	*(-2.474)*	*(1.075)*
Simple MACROSS	**9/60 MACROSS**	*0.268*	*0.170*	*0.902*	*-0.531*
		(0.430	*(0.278)*	*(0.987)*	*(-0.392)*
	12/120 MACROSS	*0.589*	*0.001*	*-0.294*	*-1.320*
		(1.617)	*(0.002)*	*(-0.530)*	*(-1.527)*
	5/260 MACROSS	*-1.606*	*0.610*	*-4.862****	*0.478*
		(-1.491)	*(0.584)*	*(-3.075)*	*(0.221)*
	9/60 MACROSS	*-0.162*	*0.092*	*-0.710*	*0.828*
		(-0.260)	*(0.151)*	*(-0.778)*	*(0.610)*
	12/120 MACROSS	*-0.474*	*0.242*	*0.514*	*1.719***
		(-1.291)	*(0.678)*	*(0.923)*	*(1.980)*
	5/260 MACROSS	*1.774*	*-0.494*	*4.997****	*-0.284*
		(1.645)	*(-0.473)*	*(3.159)*	*(-0.131)*
Exponentially weighted MACROSS	**3/12 COM MACROSS**	*-0.070*	*0.184**	*0.392***	*1.124****
		(-0.609)	*(1.677)*	*(2.339)*	*(3.621)*
	8/32 COM MACROSS	*-0.076*	*0.188**	*0.408***	*1.079****
		(-0.647)	*(1.688)*	*(2.404)*	*(3.471)*
	32/128 COM MACROSS	*0.050*	*0.336****	*0.619****	*1.326****
		(0.438)	*(3.062)*	*(3.711)*	*(4.301)*
	3/12 COM MACROSS	*0.099*	*-0.133*	*-0.381***	*-1.142****
		(0.866)	*(-1.216)*	*(-2.286)*	*(-3.693)*
	8/32 COM MACROSS	*0.094*	*-0.128*	*-0.365***	*-1.187****
		(0.804)	*(-1.153)*	*(-2.147)*	*(-3.802)*
	32/128 COM MACROSS	*0.219**	*0.019*	*-0.155*	*-0.940****
		(1.909)	*(0.172)*	*(-0.920)*	*(-3.020)*

Common risk factors	**Market**	*0.053**** *(9.286)*	*0.057**** *(10.399)*	*-0.012* *(-1.375)*	*0.051**** *(5.515)*
	GSCI	*0.025**** *(7.364)*	*0.031**** *(9.593)*	*0.011*** *(2.126)*	*0.009* *(1.632)*
	Bonds	*-0.069* *(-5.518)*	*-0.018* *(-1.445)*	*-0.030* *(-1.586)*	*-0.072**** *(-3.397)*
	SMB	*-0.009* *(-1.307)*	*-0.009* *(-1.313)*	*-0.006* *(-0.658)*	*0.022*** *(2.051)*
	HML	*-0.033**** *(-5.674)*	*-0.008* *(-1.389)*	*-0.009* *(-1.008)*	*-0.064**** *(-5.787)*
	RMW	*0.025**** *(2.721)*	*0.012* *(1.432)*	*0.031*** *(2.338)*	*-0.028* *(-1.577)*
	CMA	*-0.022** *(-1.812)*	*0.038**** *(3.480)*	*-0.046*** *(-2.554)*	*0.085**** *(3.786)*
	MOM	*-0.001* *(-0.070)*	*0.011* *(0.777)*	*0.026* *(1.325)*	*-0.002* *(-0.100)*
	R^2	***0.498***	***0.693***	***0.586***	***0.748***

TABLE 12: EXPOSURE OF LONG- AND SHORT-ONLY TREND SIGNALS TO MANAGED FUTURES RETURNS
*Notes: The values that have a gray background are related to the short-only signals. The statistical significance is presented at the 10%, 5%, and 1% levels using the asterisks *, **, and ***. The t-statistics are presented in the parentheses.*

3.4 Signal Selection

In this section, the most accurate set of signals is selected whose returns most accurately explain the returns of managed futures. Thus, the 18 trend-following signals described in Subsection 3.3.3 are chosen together with the eight conventional risk factors as a preselection of the independent variables. As stated in Subsection 3.3.3.3, it is essential to distinguish between long-only and short-only signals, as these returns best describe the returns of managed futures according to the literature and the results obtained empirically in this thesis. However, because of the large number of strongly correlated variables, as shown in Table 11, there is a risk of multicollinearity, which could inflate the outperformance of the above regression relative to the previous regressions. This problem of multicollinearity is therefore addressed by a preliminary analysis in the next subsection.

3.4.1 Multicollinearity Among the Trend-Following Signals

Because of the high correlation between individual signals described in Subsection 3.3.3.2 and since all signals are examined together in this regression, precautions should be taken to check for multicollinearity. The greater the multicollinearity, the less reliable are the estimates of the regression (Alin, 2010, p. 370).

The first test for multicollinearity used in this thesis is the most commonly used diagnosis, namely, the examination of the correlation of the explanatory variables (Alin, 2010, p. 371). As already described in Subsection 3.3.3.2, some signals have high correlations (in some cases above 0.90), so they should be further tested for multicollinearity. Therefore, the *variance inflation factor* (VIF) given in Equation 12 is employed to measure the degree of collinearity for each independent variable i (in this case, the trend-following signal). The VIF is named thus because it indicates how much the variance of the estimated coefficients increases because of collinear independent variables (Craney & Surles, 2002, p. 392).

$$VIF_i = \frac{1}{1 - R_i^2} \tag{12}$$

In this context, R_i^2 is the coefficient of multiple determination of the independent variable on the other explanatory variables. A large VIF value indicates that the independent variable is involved in at least one linear dependence; however, Alin (2010, p. 371) points out the disadvantage that it does not indicate which one. Although there are no formal criteria for when a VIF is too large, general thresholds, such as VIF above 5 or 10, are commonly used to determine if collinearity is severe enough to require corrective measures (Craney & Surles, 2002, p. 392; O'brien, 2007, p. 674). When the VIF reaches these thresholds, researchers may find that one solution to reducing collinearity is to exclude one or more variables from their analysis (O'brien, 2007, p. 674). Table 13 shows the VIFs for the independent variables, which in this case are the returns of the trend-following signals and the common asset-pricing benchmarks. This table shows that the accuracy of the estimates of the regression, which is shown in Table 12, is strongly affected by multicollinearity. The values *inf* indicate that there is even perfect multicollinearity for the exponentially weighted MACROSS signals, which means that there is a perfect linear relationship between several signals ($R_i^2 = 1$). Only the standard asset benchmarks and the passive investment factors do not exhibit serious linear relationships with other variables, as their VIF values are all below 5.

However, in this thesis, the VIF is not used as a threshold to exclude explanatory variables in order to obtain a more accurate regression coefficient. A different procedure is used to select certain variables, which is described in the next subsection. Thus, the VIF is ultimately used to detect multicollinearity and the resulting regression deficiencies.

	Managed futures indices			
	(1)	(2)	(3)	(4)
Intercept	*2.95*	*2.99*	*3.03*	*2.99*
1-month TSMOM	*2988.70*	*2796.63*	*3062.97*	*2980.45*
3-month TSMOM	*9145.67*	*8586.39*	*8365.61*	*5940.15*
12-month TSMOM	*46642.22*	*40754.20*	*40515.85*	*48190.23*
1-month TSMOM	*3096.24*	*2887.19*	*3418.97*	*3949.99*
3-month TSMOM	*7806.59*	*7379.50*	*7743.02*	*6651.01*
12-month TSMOM	*31411.28*	*28812.74*	*38412.49*	*61928.22*
9/60 MACROSS	*14509.93*	*13302.45*	*14437.00*	*21686.13*
12/120 MACROSS	*5287.35*	*4726.66*	*5619.02*	*9175.76*
5/260 MACROSS	*47635.41*	*41948.75*	*43557.77*	*52703.94*
9/60 MACROSS	*12736.12*	*11667.47*	*13206.97*	*24753.48*
12/120 MACROSS	*4143.05*	*3739.92*	*4795.96*	*9748.30*
5/260 MACROSS	*32901.75*	*30102.72*	*38411.24*	*62284.96*
3/12 COM MACROSS	*inf*	*inf*	*inf*	*inf*
8/32 COM MACROSS	*inf*	*inf*	*inf*	*inf*
32/128 COM MACROSS	*inf*	*inf*	*inf*	*inf*
3/12 COM MACROSS	*inf*	*inf*	*inf*	*inf*
8/32 COM MACROSS	*inf*	*inf*	*inf*	*inf*
32/128 COM MACROSS	*inf*	*inf*	*inf*	*inf*
Market	*2.33*	*2.27*	*2.43*	*2.16*
GSCI	*1.74*	*1.63*	*1.90*	*1.76*
Bonds	*1.78*	*1.73*	*1.77*	*1.81*
SMB	*1.15*	*1.13*	*1.20*	*1.20*
HML	*1.45*	*1.46*	*1.73*	*1.78*
RMW	*1.16*	*1.22*	*1.21*	*1.17*
CMA	*1.34*	*1.44*	*1.60*	*1.54*
MOM	*1.00*	*1.00*	*1.01*	*1.01*

TABLE 13: VARIANCE INFLATION FACTORS OF TREND-FOLLOWING SIGNALS AND COMMON RISK FACTORS
Notes: The values that have a gray background are related to the short-only signals.

3.4.2 Relaxed Lasso Regression

The main objective in this section is to select the variables that most accurately describe the returns of managed futures. For this purpose, a regularization procedure is used that will reduce the number of variables of the regression described in Subsection 3.3.3.3 and counteract the problem of multicollinearity described above. The chosen procedure is a two-stage lasso regression, known as *relaxed lasso*. The characteristics of this method and why it is appropriate in this case are described in the following discussion.

Lasso regression is a regularization method that penalizes the size of the L_1 norm of coefficients, thereby reducing some coefficients and completely excluding others. This procedure serves well in this case, since a sparser selection is made from a large number of variables and irrelevant variables are excluded. The exclusion of irrelevant variables also counteracts the problem of multicollinearity. The term lasso stands for "least absolute shrinkage and selection operator" and was first introduced by Tibshirani (1996). The goal of a lasso regression is to identify the variables and corresponding regression coefficients that result in a model that minimizes the prediction error. Lasso selection results from a restricted form of ordinary least squares regression, where the sum of the absolute values of the regression coefficients must be less than a given parameter λ. Instead of penalizing the high values of the regression coefficients, it finds out which values are irrelevant and sets them to zero. Given these properties, the lasso estimate is defined by this function:

$$\hat{\beta}^{\lambda} = \min \sum_{i=1}^{n} (Y_i - X_i^T \beta)^2 + \lambda \|\beta\|_1$$
$$\lambda \in [0, \infty) \tag{13}$$

For a sufficiently large penalty parameter λ, the chosen model is an empty set of variables, since all components of the estimator are identical to zero. In contrast, if λ is set to zero, all predictor variables are generally selected so that the model equals the regression coefficients of an ordinary linear regression.

In this work, however, a further development of lasso regression is applied. As mentioned in the beginning of this subsection, a two-stage lasso method or the relaxed lasso is used. This procedure was first introduced by Meinshausen (2007). The advantage of this two-stage model is that it can handle data with several noise variables better than the normal one-stage lasso (Meinshausen, 2007, p. 385). In addition, Hastie et al. (2017) compared different regression modeling approaches based on different measures of predictive accuracy. They concluded that the relaxed lasso outperformed the other models in almost all cases at different signal-to-noise ratios (Hastie et al., 2017, p. 17). This method is appropriate because the data in this analysis have a strong linear correlation and are thus disadvantaged by a lot of noise, which needs to be countered. Meinshausen (2007, p. 375) points out that the disadvantage of regular lasso regression is that the L_1 penalty parameter is responsible for both functions, namely, model selection and shrinkage of parameters. In contrast, the relaxed lasso uses two parameters in two successive steps. First, the λ parameter is used to select the variables, and second, the ϕ parameter (relaxation parameter) is used to shrink the remaining parameters (Meinshausen, 2007, p. 376). As a result, the relaxed lasso estimator is defined as:

$$\hat{\beta}^{\lambda,\phi} = \min \sum_{i=1}^{n} \left(Y_i - X_i^T\{\beta * \mathbf{1}_{\mathcal{M}_\lambda}\}\right)^2 + \phi\lambda\|\beta\|_1 \\ \lambda \in [0, \infty) \\ \phi \in (0, 1] \tag{14}$$

In the equation above, $\mathbf{1}_{\mathcal{M}_\lambda}$ is the indicator function on the set of variables $\mathcal{M}_\lambda \subseteq \{1, \dots, p\}$ selected by the first-stage lasso estimator $\hat{\beta}^\lambda$ so that for all $k \in \{1, \dots, p\}$, $\{\beta * \mathbf{1}_{\mathcal{M}_\lambda}\}_k = \begin{cases} 0, & k \notin \mathcal{M}_\lambda \\ \beta_k, & k \in \mathcal{M}_\lambda \end{cases}$.

As with the regular lasso, for a sufficiently large penalty parameter λ, the chosen model is an empty set of variables, since all components of the estimator are identical to zero. On the other hand, if λ is set to zero, all predictor variables are selected in general such that the model corresponds to the regression coefficients of a linear regression. If ϕ is set to 1, the lasso estimators and the relaxed lasso estimators are identical. However, for $\phi < 1$, the shrinkage of the coefficients in the selected model is reduced compared to the ordinary lasso estimator. This two-parameter approach allows more flexibility in variable selection and shrinkage penalty.

Since these two parameters are of great importance because of the assigned functions, it is important to determine them consciously. Similar to Meinshausen (2007), both parameters were determined by *k-fold cross-validation* in this thesis. Meinshausen (2007, pp. 380–385) proved that through this procedure, the cross-validated penalty parameters for the relaxed lasso estimator lead to consistent variable selection. Since trends usually extend over longer periods of several months, the parameters λ and ϕ in this thesis were determined by 4-fold cross-validation. In this process, the training data set was divided into four equal validation sets, and for each set, the optimal parameters were searched and ultimately averaged. A further split, for example, by 5- or 10-fold cross-validation, which is also conventional, could result in validation sets that are too small to capture trends, given the autocorrelation properties over different time periods discussed in Subsection 2.2.2.

3.4.3 Signal Selection Through Relaxed Lasso Regression

The variables selected by the relaxed lasso procedure and the corresponding estimated coefficients are shown in Table 14. It is immediately apparent that the number of variables for each index has been reduced from the original preselection of 26 variables to a substantial number.

The model was fit based on 70% of the respective data set for each index and then tested against the remaining 30%. These two data sets are usually referred to as the training and test data sets. In this context, the terms “in-sample” and “out-of-sample” are used as synonyms for the two data sets. For optimal parameter determination, the training data set was further split, as described in the previous subsection, using 4-fold cross-validation. Thus, for each index, the optional λ and ϕ parameters could be detected.

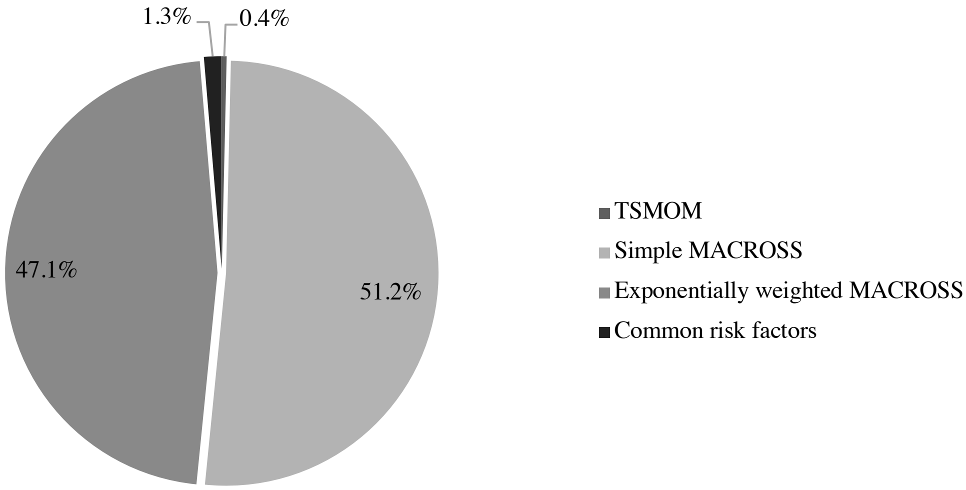
These sparser models shown in Table 14 not only provide high explanatory power for managed futures returns, but also act as stable predictors of managed futures returns over the time frame studied. This is evident when looking at the high in-sample and out-of-sample R^2 values in Table 14. The in-sample R^2 values are higher than the R^2 values obtained from the separated regressions in Section 3.3 for all but the SG CTA Mutual Fund Index (4). However, what is special about this index is that the out-of-sample R^2 value is higher than the in-sample value, which indicates that the trend-following signals can better describe the returns of this index in recent years than at the very beginning. Such a high predictive score of (out-of-sample $R^2 = 0.77$) has not been reported in the literature to date. For the other three indices, the out-of-sample R^2 values come close to the values of the regression of exponentially weighted MACROSS signals, which performed best in the separate breakdown in Section 3.3. This result implies that these relaxed lasso regressions have strong out-of-sample predictive power in addition to their better in-sample explanatory power.

		Managed futures indices			
		(1)	(2)	(3)	(4)
	Annualized alpha	*-3.89%*	*-1.79 %*	*-3.73 %*	*-4.46%*
TSMOM	**1-month TSMOM**	–	–	–	–
	3-month TSMOM	–	–	*0.055*	–
	12-month TSMOM	–	–	–	–
	1-month TSMOM	–	–	–	–
	3-month TSMOM	–	–	*0.043*	–
	12-month TSMOM	*0.017*	–	–	–
Simple MACROSS	**9/60 MACROSS**	*0.080*	–	*0.060*	–
	12/120 MACROSS	*0.114*	*0.109*	–	–
	5/260 MACROSS	–	*0.230*	–	*-0.334*
	9/60 MACROSS	–	–	*0.096*	–
	12/120 MACROSS	–	–	*0.240*	–
	5/260 MACROSS	*0.202*	*0.193*	*0.122*	*0.608*
Exponentially weighted MACROSS	**3/12 COM MACROSS**	*0.020*	–	*0.048*	–
	8/32 COM MACROSS	*0.007*	*0.192*	*0.017*	*0.412*
	32/128 COM MACROSS	*0.139*	–	*0.393*	*0.471*
	3/12 COM MACROSS	*0.001*	–	–	–
	8/32 COM MACROSS	–	*0.236*	–	–
	32/128 COM MACROSS	*0.094*	–	–	–
Common risk factors	**Market**	*0.050*	–	*-0.059*	–
	GSCI	*0.028*	–	*0.015*	–
	Bonds	*-0.082*	–	–	–
	SMB	*-0.023*	–	–	–
	HML	*-0.050*	–	*-0.031*	–
	RMW	*0.018*	–	–	–
	CMA	*-0.031*	–	–	–
	MOM	–	–	–	–
	In-sample R^2	***0.50***	***0.66***	***0.60***	***0.67***
	Out-of-sample R^2	***0.48***	***0.62***	***0.49***	***0.77***

TABLE 14: EXPOSURE OF RELAXED LASSO VARIABLES TO MANAGED FUTURES RETURNS
*Notes: The values that have a gray background are related to the short only signals. The statistical significance is presented at the 10%, 5%, and 1% levels using the asterisks *, **, and ***.*

The results from Table 14 present evidence that most of the exposure of managed futures returns is accumulated through MACROSS strategies. The simple MACROSS returns have the highest variable coefficients and thus the greatest relative importance of 51.2% in explaining managed futures returns across all examined indices. This is followed closely by the exponentially weighted MACROSS with 47.1%. Furthermore, the TSMOM signals and the conventional risk factors show almost no influence on the returns of managed futures. This is also illustrated in Figure 15 where the exposures between trend-following signals are put into relative terms along with the common risk factors.

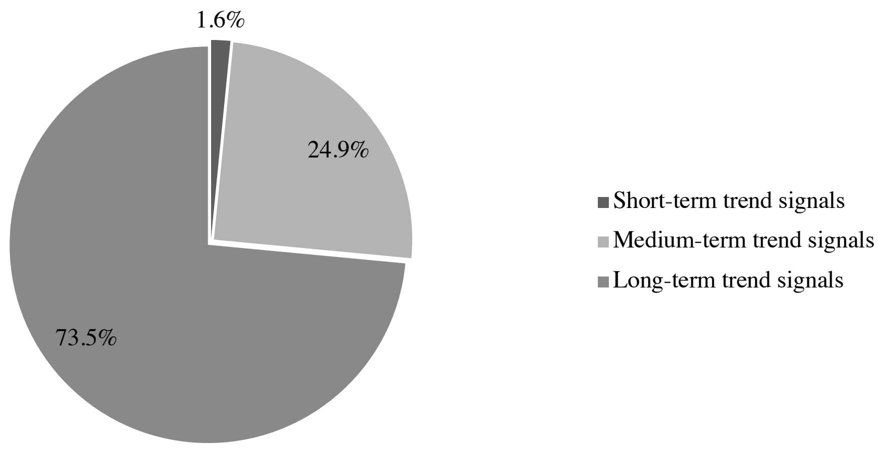
FIGURE 15: MANAGED FUTURES EXPOSURES ACROSS TREND SIGNALS AND COMMON RISK FACTORS



Notes: This figure compares and categorizes the regression coefficients from the relaxed lasso regressions of each managed futures index on the variables explained in this section. The regression coefficients are scaled by their squared sum to account for negative exposure and to show their relative significance.

In addition, the relaxed lasso regressions demonstrate the relative importance of short-, medium-, and long-term trends for managed futures funds. This result is shown in Figure 16 and fits the return characteristics described in Subsection 3.2.4 and the separated regression results in Section 3.3.3. Managed futures returns were most influenced by long-term trend signals, with a relative weight of 73.5% compared to the other two trend horizons. However, at 24.9%, the medium-term trend horizon still shows a respectable influence, suggesting that CTAs are likely invested in different trend horizons to gain diversification benefits made possible by the pairwise correlations described in Subsections 3.2.4.1 and 3.3.3.2.

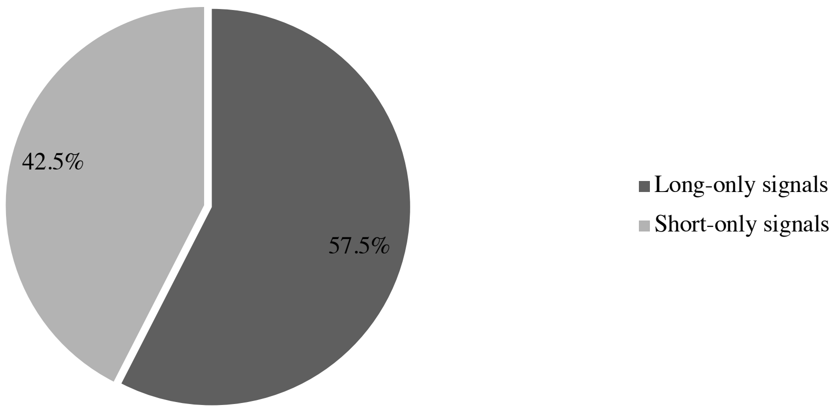
FIGURE 16: MANAGED FUTURES EXPOSURES ACROSS TREND HORIZONS



Notes: This figure compares and categorizes the regression coefficients from the relaxed lasso regressions of each managed futures index on the variables explained in this section. The regression coefficients are scaled by their squared sum to account for negative exposure and to show their relative significance.

Another takeaway from these relaxed lasso regressions is that it can be difficult for managed futures to profitably establish and maintain short positions. As shown in Figure 17 managed futures returns are more exposed to long-only signals with a weight of 57.5%, meaning they are more invested in long than short trend signals. However, with a weighting of 42.5%, the influence of short trend signals cannot be ignored. Although these signals have drastically weaker returns than the long side, they still seem to have a large impact on managed futures returns. Possibly, CTAs keep these investments for hedging or diversification benefits because of the negative correlation coefficients described in Subsection 3.3.3.2. Another reason for this imbalance could be the distribution of long- and short-selling trends during the analyzed time series shown in Figure 14, especially since CTAs seemed to favor long-term trends.

FIGURE 17: MANAGED FUTURES EXPOSURES ACROSS LONG- AND SHORT-ONLY SIGNALS



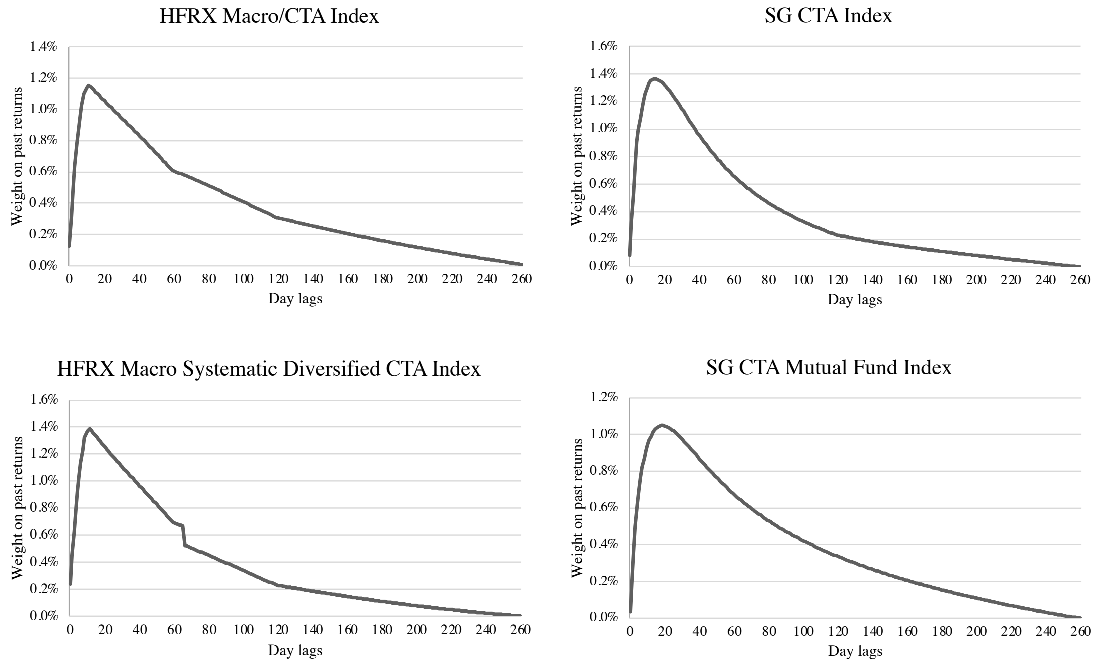
Notes: This figure compares and categorizes the regression coefficients from the relaxed lasso regressions of each managed futures index on the variables explained in this section. The regression coefficients are scaled by their squared sum to account for negative exposure and to show their relative significance.

3.4.4 Return Signature Plots Derived From Relaxed Lasso Regression

The estimated return signal plots for the managed futures exposure are shown in Figure 18. The shapes of these empirical weighting coefficients are comparable directly to the theoretical return signature plots of the three trend-following signal types described in this thesis (see Figures 2, 6, and 9). Given the relative weight distribution between trend signals shown in Figure 15 it is not surprising that the return signature plots resemble a mixture of the simple and exponentially weighted MACROSS signature plots. As described in the previous subsection, the simple MACROSS dominates the representation of weights.

The idea proposed by Boos and Grob (2022, p. 9) emerges as plausible in this respect. They state that the weighting of the returns of the first days' increases and then decreases after a certain time period could stem, among other things, from the spread of MACROSS strategies. It is interesting to note that each return signature plot depicted in Figure 18 peaks just after the 10-day mark. This suggests that a shorter MA^{fast}, similar to this 10-day time range, is preferred by professional CTAs. However, with the selected slow moving average, the result does not look so consistent. It is not sufficiently clear to identify the time period of the MA^{slow} to which CTAs tend to move.

FIGURE 18: RETURN SIGNATURE PLOTS BASED ON RELAXED LASSO REGRESSION COEFFICIENTS



Notes: These plots illustrate how much weight the managed futures indices assign to past returns dependent on the exposure to each trend-following signal. All weights are normalized and sum up to 1. These illustrations are modeled after the approach of Levine and Pedersen (2016).

4 Conclusion

The conclusion discusses the main findings of this thesis. In Section 4.1, the research question formulated in the introduction is answered. In addition, the results are discussed and interpreted comprehensively. For this purpose, the current state of knowledge from the literature review is linked to the empirical results. Section 4.2 deals with the restrictions of this thesis. Finally, implications for further research are derived in the last section.

4.1 Discussion of Results

This thesis has aimed to provide a thorough insight into the methodology of managed futures, whose investment practices are highly confidential. The current state of the literature shows that TSMOM explains managed futures returns to a large extent. However, recent academic evidence has shown that the weighting coefficients of daily returns of speculators in futures markets do not resemble the weighting of TSMOM strategies. They are more similar to the more dynamic moving average crossover strategies. Based on this information, it was hypothesized that MACROSS signals can replicate the returns of CTAs better than TSMOM. The research question posed at the beginning is also connected to this proposition:

– *Which trend-following signals most significantly explain managed futures returns?*

To answer this question, three common trend-following strategies were first developed and analyzed for different futures contracts and currency pairs. These three strategies were TSMOM, simple MACROSS, and exponentially weighted MACROSS. Subsequently, these strategies were further divided into short-, medium-, and long-term trend signals. Previous research has shown that returns increase when the look-back period is extended up to 12 months, but this finding was studied only for the TSMOM signals. In this thesis, it has been confirmed that this feature of higher returns for longer look-back periods is also true for the MACROSS strategies. Furthermore, the findings in this thesis show that the TSMOM signals have higher risk-weighted returns than the two MACROSS signals over all three comparable periods. Comparing all signals with conventional passive investments in different markets and common risk factors, there is a positive significant alpha left for each signal and each look-back period. This result is evidence of the presence and importance of momentum for the three trend-following strategies and shows low exposure to common investment factors.

Although they have weaker performance, the returns of MACROSS strategies can better describe the returns of managed futures. In the separate regressions, the exponentially weighted MACROSS strategy produced the highest regression scores for all managed futures indices. This finding also corresponds to the hypothesis mentioned at the beginning of this section. However, to obtain further insight into the approach of CTAs, further analysis was conducted.

Subsequently, these regressions were adjusted for different approaches to risk forecasting to provide an overview of which risk approaches are most likely to be considered by CTAs. In this analysis, it was shown that the chosen observation periods of the volatility calculation used in the existing literature were too long. Shorter volatility observation periods replicate the returns of managed futures better. This finding shows strong similarities to the widely used RiskMetrics risk calculation approach.

Using this more optimal risk approach, the effect of each instrument on managed futures returns was also examined. This examination produced interesting findings on the money allocation of the CTAs. For each asset class, namely, commodities, equities, bonds, and currencies, a different pattern can be identified. However, these patterns do not seem to depend on the liquidity or expected performance of the respective asset. In the case of liquidity, however, it could be because the instruments analyzed already belong to liquid contracts.

Another finding from the literature examined in this thesis is that when long- and short-only trend-following strategies are separated, the returns of managed futures can be better explained. However, this finding had so far been verified only in a variation of the TSMOM strategy, and the signals were differentiated by asset class and not by look-back period, as has been done in this thesis. In addition, passive investment and conventional risk factors are included in the analysis. The regressions of these split trend-following signals and investment and risk factors show improved R^2 values compared to the described separate regressions of the trend-following profiles. However, the coefficients of these regressions are not robust because of high multicollinearity among the variables. To overcome this problem, a relaxed lasso procedure was used to exclude certain variables in a first pass and then further shrink the remaining ones in the second pass. This resulted in more representable regressions with a targeted selection of trend signals that not only accurately described the returns of managed futures but could also predict them to some degree.

Further insights resulted from signal selection by relaxed lasso regression. As previously conjectured, the returns of managed futures are more exposed to the returns of MACROSS trend signals. The MACROSS strategies account for most of the sum of the coefficients. There is a slightly higher representation of the simple MACROSS signals than of the exponentially weighted signals. Besides, the returns of the CTAs do not seem to be influenced much by the TSMOM signals or conventional factors. The impact of the influential signals is also most on the long-term trend signals. This is justifiable when comparing the performance benefits of the different look-back periods, as the longer-term periods have the highest Sharpe ratios. Furthermore, as in the literature, there is a slight bias toward the long-only signals. CTAs are more invested in the long side of trend signals.

In conclusion, with respect to the overarching research question, moving average crossover signals can best explain the returns of managed futures. It is important to differentiate between the long- and short-only sides, as CTAs show a slight long-only bias. Furthermore, the focus should be on the longer-term trend signals with look-back periods up to 12 months or similar, as these time periods exhibit much stronger coefficients in all regressions.

4.2 Limitations of Study

The returns of the trend-following strategies constructed in this thesis are all gross of transaction and management fees. However, these costs play a crucial role in the context of hedge fund industry practice. This aspect would therefore need to be built into these strategies in a further study to further confirm the results described above.

Another restriction in this thesis was the choice of currency pairs. Although the most liquid currencies were considered and implemented in the trend-following strategies, only currency-pairs against the USD were considered. However, in practice, it is also a feasible option to trade other liquid cross-country currency pairs.

4.3 Implications for Further Research

As demonstrated in the discussion of results, based on the previous empirical knowledge, this study has scientifically attempted and to a high degree further revealed the approaches of CTAs. However, as described in the section above, transaction and management fees should be included in a further study. The focus could, for example, be on analyzing the trend signals examined in this thesis with respect to turnover costs. Hypothetically, one could assume that the technical MACROSS strategies cause a lower turnover in comparison to time series momentum strategies, since these are preferred by CTAs according to the results of this study.

Furthermore, the trend-following strategies analyzed in this thesis can be used as a basis for further variations of trend signals. The results of this thesis should therefore be understood as a fundamental reference for future variations.

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Appendix

Appendix A – Detailed Overview of Data

Table A1 provides a detailed overview of all futures contracts and currency pairs, all of which were obtained from Bloomberg as of the beginning of 1999. Thereby, the Bloomberg ticker, the associated exchange and for the exchange traded instruments the average daily volume of the last 12 months are shown.

Instrument		Bloomberg Ticker	Exchange	Average daily volume (TTM)
Commodities				
Energy	WTI	CL1	New York Mercantile Exchange (NYMEX)	345928
	Gasoline	XB1	New York Mercantile Exchange (NYMEX)	48226
	Heating Oil	HO1	New York Mercantile Exchange (NYMEX)	41539
	Natural Gas	NG1	New York Mercantile Exchange (NYMEX)	121815
	Brent	CO1	ICE Futures Europe	239313
	Crude	QS1	ICE Futures Europe	69698
Grains	Corn	C 1	Chicago Board of Trade (CBOT)	135024
	Chicago Wheat	W 1	Chicago Board of Trade (CBOT)	46142
	Kansas Wheat	KW1	Chicago Board of Trade (CBOT)	19672
	Soybeans	S 1	Chicago Board of Trade (CBOT)	84899
	Soybean meal	SM1	Chicago Board of Trade (CBOT)	39242
	Soybean Oil	BO1	Chicago Board of Trade (CBOT)	36894
Livestock	Live Cattle	LC1	Chicago Mercantile Exchange (CME)	15514
	Feeder Cattle	FC1	Chicago Mercantile Exchange (CME)	20494
	Lean Hogs	LH1	Chicago Mercantile Exchange (CME)	4948
Softs	Sugar	SB1	ICE Futures US	53386
	Coffe	KC1	ICE Futures US	16137
	Cotton	CT1	ICE Futures US	10290
	Cocoa	CC1	ICE Futures US	16974
Metals	Gold	GC1	New York Commodities Exchange (COMEX)	149224
	Silver	SI1	New York Commodities Exchange (COMEX)	53633
	Platinum	PL1	New York Commodities Exchange (COMEX)	16277
	Copper	HG1	New York Commodities Exchange (COMEX)	56327
Equities				
Americas	Dow Jones mini	DM1	Chicago Board of Trade (CBOT)	169784
	S&P 500 mini	ES1	Chicago Mercantile Exchange (CME)	1543287
	NASDAQ 100 mini	NQ1	Chicago Mercantile Exchange (CME)	565419
	S&P/TSX 60	PT1	Montreal Exchange (MX)	23196
	MEX IPC	IS1	Mercado Mexicano de Derivados	1010
	IBOVESPA	BZ1	B3 Derivatives	159644

EMEA	EURO STOXX 50	VG1	Eurex Exchange	749337
	FTSE 100	Z 1	ICE Futures Europe	94821
	CAC 40	CF1	Euronext Derivatives Paris	47649
	DAX	GX1	Eurex Exchange	57436
	IBEX 35	IB1	Meff Renta Variable	10046
	FTSE MIV	ST1	Borsa Italiana (IDEM)	16406
	AEX	EO1	Euronext Derivatives Amsterdam	12413
	OMX STKH30	QC1	OMX Nordic Exchange Stockholm	72232
	SWISS MKT	SM1	Eurex Exchange	29007
Asia/Pacific	NIKKEI 225 (OSE)	NK1	Osaka Exchange	57225
	HANG SENG	HI1	Hong Kong Futures Exchange	25225
	CSI 300	IFB1	China Financials Futures Exchange	46456
	S&P/ASX	XP1	ASX Trade24	43955
Bonds				
North/Latin America	US ULTRA BOND	WN1	Chicago Board of Trade (CBOT)	192823
	US LONG BOND	US1	Chicago Board of Trade (CBOT)	368416
	US 10YR ULTRA FUT	UXY1	Chicago Board of Trade (CBOT)	331629
	US 10YR NOTE	TY1	Chicago Board of Trade (CBOT)	1644952
	US 5YR NOTE	FV1	Chicago Board of Trade (CBOT)	1093197
	US 2YR NOTE	TU1	Chicago Board of Trade (CBOT)	537739
	CAN 10YR BOND FUT	CN1	Montreal Exchange (MX)	120620
Europe/Africa	EURO-BUXL 30Y BND	UB1	Eurex Exchange	79845
	EURO-BUND FUTURE	RX1	Eurex Exchange	745608
	EURO-BOBL FUTURE	OE1	Eurex Exchange	522746
	EURO-SCHATZ	DU1	Eurex Exchange	417066
	LONG GILT FUTURE	G 1	ICE Futures Europe	241739
	Eur-BTP Future	IK1	Eurex Exchange	144884
	Euro-OAT Future	OAT1	Eurex Exchange	185565
Asia/Pacific	JPN 10Y BOND	JB1	Osaka Exchange (OSE)	25660
Currencies (Carry Return Index Bloomberg)				
	AUD/USD	AUDUSDCR		
	EUR/USD	EURUSDCR		
	CAD/USD	CADUSDCR		
	JPY/USD	JPYUSDCR		
	NOK/USD	NOKUSDCR		
	NZD/USD	NZDUSDCR		
	SEK/USD	SEKUSDCR		
	CHF/USD	CHFUSDCR		
	GBP/USD	GBPUSDCR		
	DKK/USD	DKKUSDCR		

TABLE A1: DETAILED OVERVIEW OF CONSIDERED DATA

Appendix B – Performance Analysis of Trend-Following Strategies

Appendix B1 – Alpha Regressions of Symmetric Trend-Following Signals

This section contains additional information to the performance analysis of the trend signals in Subsection 3.2.4. In this context, Table B1 shows the regression coefficients, of the regression for the calculation of the alphas reported in Table 5. In Table B1, the look-back periods are abbreviated as (1) for the short-term horizon, (2) for the medium-term horizon, and (3) for the long-term horizon.

	TSMOM			**Simple MACROSS**			**Exponentially weighted MACROSS**		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Intercept	*0.001****	*0.000****	*0.001****	*0.000***	*0.000***	*0.001****	*0.001****	*0.000***	*0.000***
	(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*
Market	*-0.249****	*-0.237****	*-0.147****	*-0.229****	*-0.204****	*-0.181****	*-0.254****	*-0.225****	*-0.081****
	(.012)	*(.012)*	*(.012)*	*(.012)*	*(.012)*	*(.012)*	*(.012)*	*(.012)*	*(.012)*
GSCI	*-0.027****	*-0.003*	*0.020***	*-0.01*	*0.011*	*0.013**	*-0.022****	*-0.004*	*0.024****
	(.008)	*(.008)*	*(.008)*	*(.008)*	*(.008)*	*(.008)*	*(.008)*	*(.008)*	*(.008)*
Bonds	*0.272****	*0.265****	*0.389****	*0.265****	*0.271****	*0.359****	*0.269****	*0.292****	*0.385****
	(.026)	*(.026)*	*(.026)*	*(.027)*	*(.027)*	*(.026)*	*(.026)*	*(.027)*	*(.026)*
SMB	*0.073****	*0.126****	*0.125****	*0.119****	*0.120****	*0.128****	*0.095****	*0.123****	*0.127****
	(.018)	*(.018)*	*(.018)*	*(.019)*	*(.019)*	*(.018)*	*(.018)*	*(.019)*	*(.018)*
HML	*0.021*	*-0.017*	*-0.131****	*-0.004*	*-0.043***	*-0.096****	*0.027**	*-0.030**	*-0.129****
	(.016)	*(.016)*	*(.016)*	*(.017)*	*(.017)*	*(.016)*	*(.016)*	*(.017)*	*(.016)*
RMW	*-0.041**	*0.017*	*0.017*	*-0.011*	*0.012*	*0.028*	*-0.035*	*0.006*	*0.059***
	(.023)	*(.023)*	*(.023)*	*(.024)*	*(.024)*	*(.023)*	*(.023)*	*(.024)*	*(.023)*
CMA	*0.015*	*0.118****	*0.253****	*0.097****	*0.169****	*0.243****	*0.039*	*0.155****	*0.236****
	(.03)	*(.03)*	*(.03)*	*(.031)*	*(.031)*	*(.03)*	*(.03)*	*(.031)*	*(.03)*
MOM	*-0.061*	*-0.042*	*-0.049*	*-0.031*	*-0.023*	*-0.048*	*-0.070**	*-0.032*	*-0.019*
	(.038)	*(.039)*	*(.039)*	*(.039)*	*(.04)*	*(.039)*	*(.038)*	*(.04)*	*(.039)*
R^2	**0.118**	**0.114**	**0.101**	**0.103**	**0.092**	**0.109**	**0.12**	**0.109**	**0.077**

TABLE B1: PASSIVE INVESTMENT AND COMMON RISK FACTORS REGRESSED ON TREND-FOLLOWING SIGNALS
*Notes: The statistical significance is presented at the 10%, 5% and 1% levels using the asterisks *, ** and ***. Besides, standard errors are in the parentheses.*

Appendix B2 – Alpha Regressions of Asymmetric Trend-Following Signals

This section provides supplementary information to the performance analysis of the long- and short-only trend signals in subsection 3.3.3.1. In this context, Table B2 and B3 show the regression coefficients, of the regression for the calculation of the alphas reported in Table 10. In Tables B2 and B3, the look-back periods are abbreviated as (1) for the short-term horizon, (2) for the medium-term horizon, and (3) for the long-term horizon.

	TSMOM			**Simple MACROSS**			**Exponentially weighted MACROSS**		
	(1)	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**	**(1)**	**(2)**	**(3)**
Intercept	*0.000****	*0.000***	*0.000****	*0.000***	*0.000***	*0.000****	*0.000****	*0.000***	*0.000***
	(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*
Market	*0.143****	*0.152****	*0.179****	*0.158****	*0.167****	*0.169****	*0.142****	*0.159****	*0.210****
	(.008)	*(.008)*	*(.008)*	*(.008)*	*(.009)*	*(.009)*	*(.008)*	*(.008)*	*(.009)*
GSCI	*0.120****	*0.133****	*0.141****	*0.130****	*0.140****	*0.139****	*0.124****	*0.133****	*0.143****
	(.005)	*(.005)*	*(.006)*	*(.005)*	*(.006)*	*(.006)*	*(.005)*	*(.006)*	*(.006)*
Bonds	*0.756****	*0.753****	*0.810****	*0.753****	*0.756****	*0.798****	*0.757****	*0.769****	*0.814****
	(.017)	*(.018)*	*(.019)*	*(.018)*	*(.019)*	*(.019)*	*(.018)*	*(.019)*	*(.019)*
SMB	*0.083****	*0.110****	*0.105****	*0.106****	*0.107****	*0.108****	*0.095****	*0.109****	*0.105****
	(.012)	*(.013)*	*(.013)*	*(.013)*	*(.013)*	*(.013)*	*(.012)*	*(.013)*	*(.013)*
HML	*-0.021**	*-0.038****	*-0.099****	*-0.032****	*-0.053****	*-0.081****	*-0.017*	*-0.046****	*-0.100****
	(.011)	*(.011)*	*(.012)*	*(.011)*	*(.012)*	*(.012)*	*(.011)*	*(.012)*	*(.012)*
RMW	*-0.01*	*0.02*	*0.019*	*0.007*	*0.018*	*0.024*	*-0.005*	*0.015*	*0.037***
	(.015)	*(.016)*	*(.017)*	*(.016)*	*(.017)*	*(.017)*	*(.016)*	*(.017)*	*(.017)*
CMA	*0.099****	*0.148****	*0.218****	*0.139****	*0.177****	*0.215****	*0.110****	*0.170****	*0.211****
	(.02)	*(.021)*	*(.022)*	*(.021)*	*(.022)*	*(.022)*	*(.02)*	*(.022)*	*(.022)*
MOM	*-0.021*	*-0.012*	*-0.017*	*-0.008*	*-0.003*	*-0.015*	*-0.028*	*-0.007*	*-0.004*
	(.026)	*(.027)*	*(.028)*	*(.027)*	*(.028)*	*(.028)*	*(.026)*	*(.028)*	*(.028)*
R^2	*0.388*	*0.379*	*0.406*	*0.378*	*0.379*	*0.393*	*0.383*	*0.376*	*0.418*

TABLE B2: PASSIVE INVESTMENT AND COMMON RISK FACTORS REGRESSED ON LONG-ONLY TREND-FOLLOWING SIGNALS

*Notes: The statistical significance is presented at the 10%, 5% and 1% levels using the asterisks *, ** and ***. Besides, standard errors are in the parentheses.*

	TSMOM			Simple MACROSS			Exponentially weighted MACROSS		
	(1)	(2)	(3)	(1)	(2)	(3)	(1)	(2)	(3)
Intercept	*0.000***	*0.000**	*0.000****	*0*	*0*	*0.000***	*0.000***	*0.000**	*0*
	(.000)	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*	*(.000)*
Market	*-0.336****	*-0.326****	*-0.296****	*-0.321****	*-0.311****	*-0.306****	*-0.337****	*-0.320****	*-0.269****
	(.007)	*(.007)*	*(.006)*	*(.007)*	*(.007)*	*(.006)*	*(.007)*	*(.007)*	*(.006)*
GSCI	*-0.139****	*-0.127****	*-0.119****	*-0.130****	*-0.120****	*-0.120****	*-0.136****	*-0.127****	*-0.117****
	(.005)	*(.004)*	*(.004)*	*(.005)*	*(.004)*	*(.004)*	*(.005)*	*(.004)*	*(.004)*
Bonds	*-0.465****	*-0.467****	*-0.403****	*-0.468****	*-0.463****	*-0.415****	*-0.467****	*-0.454****	*-0.409****
	(.016)	*(.015)*	*(.014)*	*(.015)*	*(.015)*	*(.014)*	*(.015)*	*(.015)*	*(.014)*
SMB	*-0.005*	*0.022***	*0.015*	*0.018**	*0.019**	*0.018**	*0.007*	*0.021***	*0.017**
	(.011)	*(.01)*	*(.01)*	*(.011)*	*(.01)*	*(.01)*	*(.011)*	*(.01)*	*(.01)*
HML	*0.043****	*0.026****	*-0.038****	*0.032****	*0.01*	*-0.020***	*0.047****	*0.018**	*-0.036****
	(.01)	*(.009)*	*(.009)*	*(.01)*	*(.009)*	*(.009)*	*(.01)*	*(.009)*	*(.009)*
RMW	*-0.02*	*0.009*	*0.008*	*-0.004*	*0.007*	*0.013*	*-0.016*	*0.004*	*0.026***
	(.014)	*(.013)*	*(.013)*	*(.014)*	*(.013)*	*(.012)*	*(.014)*	*(.013)*	*(.012)*
CMA	*-0.074****	*-0.024*	*0.050****	*-0.033**	*0.006*	*0.046****	*-0.062****	*-0.003*	*0.039***
	(.018)	*(.017)*	*(.017)*	*(.018)*	*(.017)*	*(.016)*	*(.018)*	*(.017)*	*(.016)*
MOM	*-0.041**	*-0.031*	*-0.036**	*-0.027*	*-0.022*	*-0.034*	*-0.047***	*-0.026*	*-0.022*
	(.023)	*(.022)*	*(.021)*	*(.023)*	*(.022)*	*(.021)*	*(.023)*	*(.022)*	*(.021)*
R^2	*0.519*	*0.529*	*0.51*	*0.51*	*0.509*	*0.527*	*0.522*	*0.522*	*0.496*

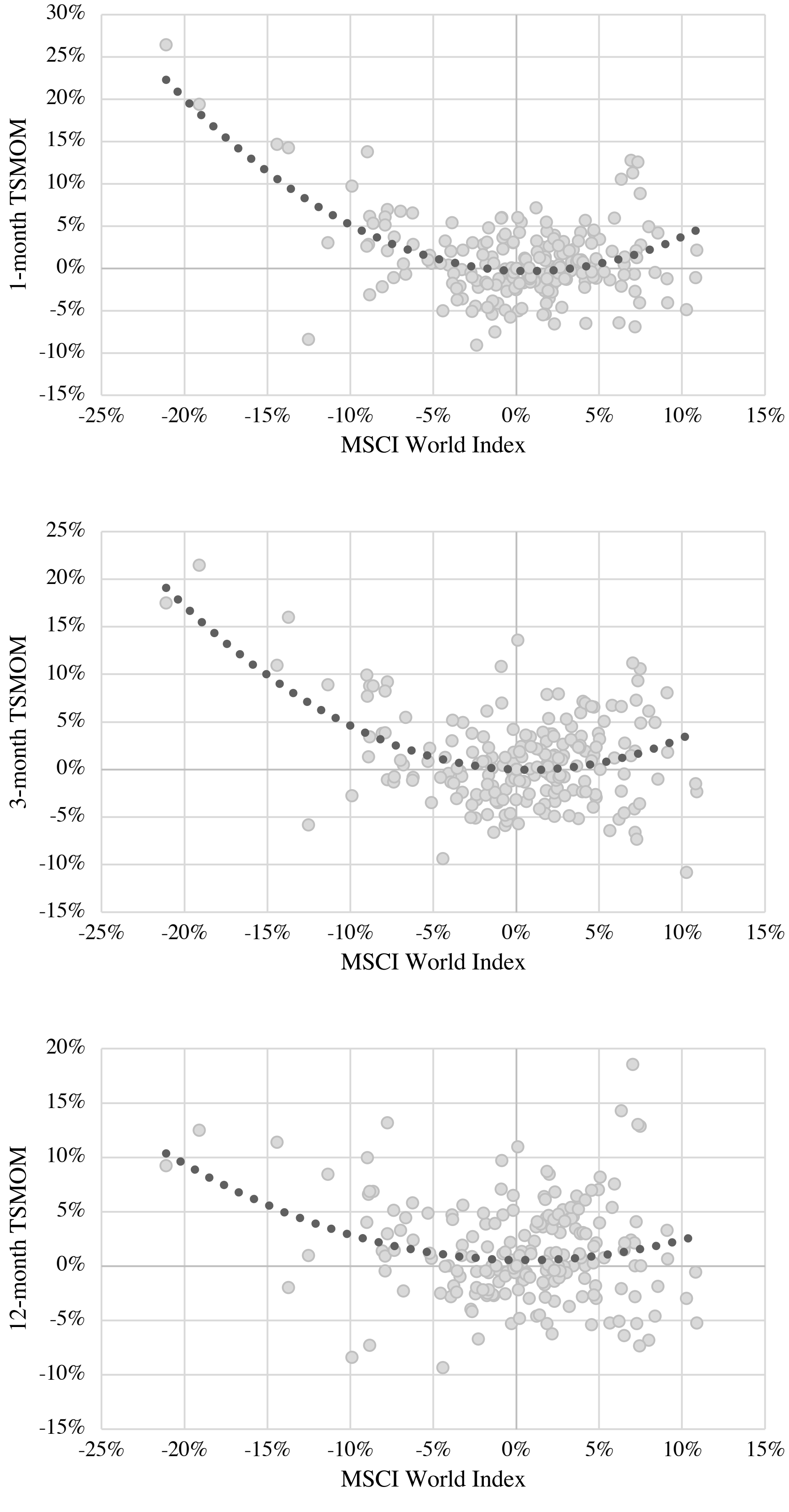
TABLE B3: PASSIVE INVESTMENT AND COMMON RISK FACTORS REGRESSED ON SHORT-ONLY TREND-FOLLOWING SIGNALS

*Notes: The statistical significance is presented at the 10%, 5% and 1% levels using the asterisks *, ** and ***. Besides, standard errors are in the parentheses.*

Appendix B3 – Trend-Following Strategies against the Market

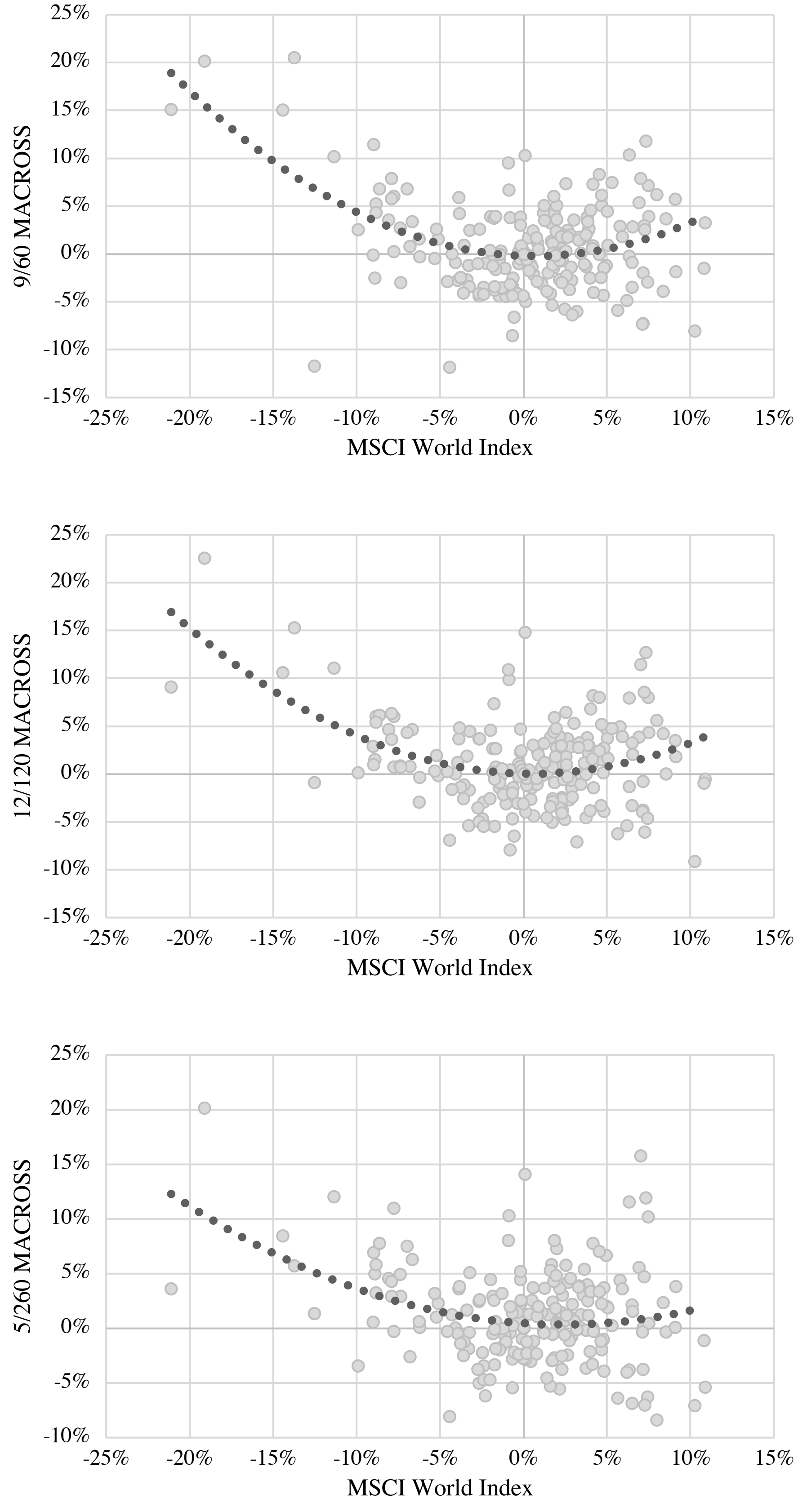
Figures B1 to B3 show the smile curves described in Subsection 3.2.4 for all trend following strategies considered over all look-back periods. They are quite similar across trend horizons and show comparable performance against monthly MSCI World excess returns.

FIGURE B1: TIME SERIES MOMENTUM STRATEGIES AGAINST THE MARKET



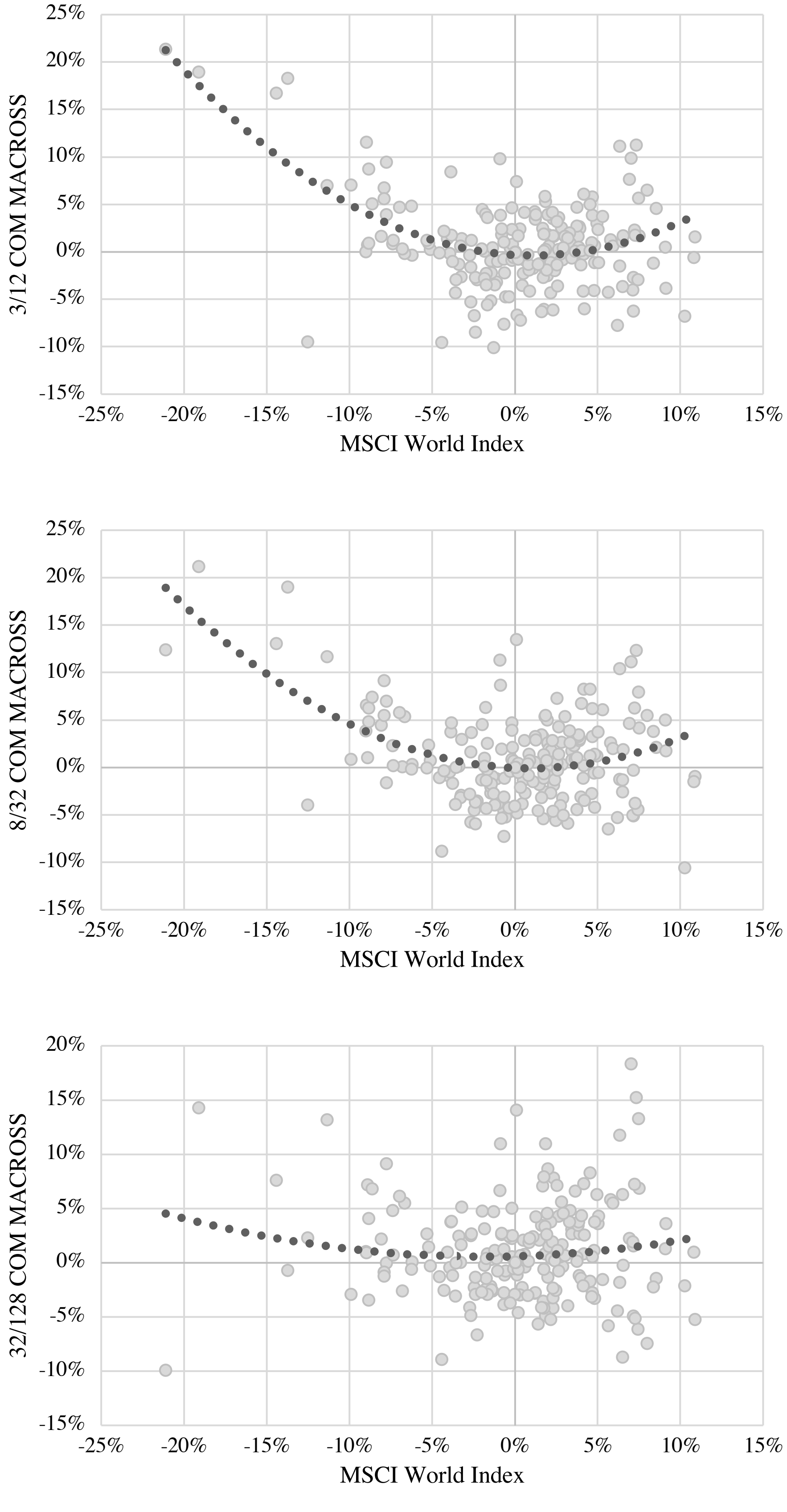
Notes: These charts show the monthly excess returns of all time series momentum strategies considered compared to the MSCI World Index from 1999 to 2022. The dark-gray dotted line represents a quadratic fit in each graph.

FIGURE B2: SIMPLE MACROSS STRATEGIES AGAINST THE MARKET



Notes: These charts show the monthly excess returns of all simple MACROSS strategies considered compared to the MSCI World Index from 1999 to 2022. The dark-gray dotted line represents a quadratic fit in each graph.

FIGURE B3: EXPONENTIALLY WEIGHTED MACROSS STRATEGIES AGAINST THE MARKET



Notes: These charts show the monthly excess returns of all exponentially weighted MACROSS strategies considered compared to the MSCI World Index from 1999 to 2022. The dark-gray dotted line represents a quadratic fit in each graph.

Appendix C – Exposure to Various Assets

This section provides supplementary detail on the analysis of the impact of each of the instruments considered on the returns of the managed futures indices in Subsection 3.3.2. Table C1 contains all the regression coefficients of each instrument explaining the managed futures indices. The indices are abbreviated as (1) for the HFRX Macro/CTA Index, (2) for the SG CTA Index, (3) for the HFRX Macro Systematic Di-versified CTA Index, and (4) for the SG CTA Mutual Fund Index. The independent variables in this table are sorted in alphabetical order by Bloomberg tickers, which are listed in Table A1. These coefficients were compared in Figures 10 and 11.

	Managed futures indices			
	(1)	**(2)**	**(3)**	**(4)**
Intercept	*-0.000***	*-0.000*	*-0.000*	*-0.000***
	(0.000)	*(0.000)*	*(0.000)*	*(0.000)*
AUD/USD	*0.008****	*0.009****	*0.018****	*0.028****
	(.002)	*(.003)*	*(.003)*	*(.003)*
Soybean Oil	*0.001*	*-0.001*	*0.001*	*0.008****
	(.002)	*(.002)*	*(.003)*	*(.003)*
IBOVESPA	*0.007****	*0.007****	*0.013****	*0.016****
	(.002)	*(.002)*	*(.003)*	*(.003)*
Corn	*-0.001*	*0.001*	*-0.001*	*0.009****
	(.002)	*(.002)*	*(.003)*	*(.003)*
CAD/USD	*0.004**	*0.003*	*0.008***	*0.015****
	(.002)	*(.002)*	*(.003)*	*(.003)*
Cocoa	*0.009****	*0.006****	*0.004*	*0.006***
	(.002)	*(.002)*	*(.002)*	*(.003)*
CAC 40	*-0.002*	*-0.002*	*-0.010**	*-0.008*
	(.004)	*(.004)*	*(.006)*	*(.006)*
CHF/USD	*0.007****	*0.013****	*0.012****	*0.013****
	(.002)	*(.002)*	*(.002)*	*(.002)*
WTI	*0.005****	*0.011****	*0.006***	*0.009****
	(.002)	*(.002)*	*(.002)*	*(.002)*
CAN 10YR BOND FUT	*0.001*	*0.004**	*-0.006***	*0.003*
	(.002)	*(.002)*	*(.003)*	*(.003)*
Brent	*0.004**	*0.006***	*0.004*	*-0.004*
	(.002)	*(.003)*	*(.004)*	*(.003)*
Cotton	*0.000*	*0.003**	*-0.003*	*0.001*
	(.002)	*(.002)*	*(.002)*	*(.003)*

DKK/USD	*0.003* *(.01)*	*0.017** *(.009)*	*-0.011* *(.012)*	*0.009* *(.014)*
Dow Jones mini	*0.008*** *(.004)*	*0.008*** *(.004)*	*-0.006* *(.006)*	*0.011** *(.006)*
EURO-SCHATZ	*0.009**** *(.003)*	*0.014**** *(.003)*	*0.022**** *(.004)*	*0.015**** *(.004)*
AEX	*0.017**** *(.003)*	*0.004* *(.003)*	*0.032**** *(.005)*	*0.010*** *(.005)*
S&P 500 mini	*0.009*** *(.004)*	*0.016**** *(.004)*	*0.035**** *(.007)*	*0.030**** *(.007)*
EUR/USD	*0.001* *(.01)*	*-0.011* *(.009)*	*0.009* *(.012)*	*-0.012* *(.014)*
Feeder Cattle	*0* *(.002)*	*-0.002* *(.002)*	*-0.003* *(.003)*	*0.003* *(.003)*
US 5YR NOTE	*0.009*** *(.004)*	*0.014**** *(.005)*	*0.009* *(.007)*	*0.027**** *(.008)*
LONG GILT FUTURE	*0.005*** *(.002)*	*0.009**** *(.002)*	*0.005** *(.003)*	*0.003* *(.003)*
GBP/USD	*0.002* *(.002)*	*0.012**** *(.002)*	*0.007**** *(.003)*	*0.009**** *(.003)*
Gold	*0.025**** *(.002)*	*0.023**** *(.002)*	*0.029**** *(.003)*	*0.025**** *(.003)*
DAX	*0.004* *(.003)*	*0.008*** *(.003)*	*0.012**** *(.004)*	*0.015**** *(.004)*
Copper	*0.003** *(.002)*	*0.010**** *(.002)*	*0.008**** *(.003)*	*0.020**** *(.003)*
HANG SENG	*0.017**** *(.002)*	*0.016**** *(.002)*	*0.016**** *(.003)*	*0.022**** *(.003)*
Heating Oil	*0.008**** *(.003)*	*0.009**** *(.003)*	*0.010**** *(.004)*	*0.012**** *(.004)*
IBEX 35	*-0.003* *(.002)*	*-0.001* *(.003)*	*-0.001* *(.003)*	*0.001* *(.004)*
CSI 300	*0.004*** *(.002)*	*0.009**** *(.002)*	*0.009**** *(.003)*	*0.007**** *(.003)*
Eur-BTP Future	*0.012**** *(.002)*	*0.017**** *(.003)*	*0.017**** *(.003)*	*0.010**** *(.003)*
MEX IPC	*-0.003** *(.002)*	*-0.009**** *(.002)*	*-0.001* *(.003)*	*-0.002* *(.003)*
JPN 10Y BOND	*0.004**** *(.002)*	*0.012**** *(.002)*	*0.013**** *(.002)*	*0.010**** *(.003)*
JPY/USD	*0.011**** *(.002)*	*0.022**** *(.002)*	*0.014**** *(.003)*	*0.016**** *(.003)*
Coffe	*0.002* *(.002)*	*0.005*** *(.002)*	*0.005*** *(.002)*	*0.012**** *(.003)*

Kansas Wheat	*0.004**	*0.006***	*0.008***	*0.012****
	(.002)	*(.003)*	*(.004)*	*(.004)*
Live Cattle	*0.003**	*0.005***	*0.008****	*0.010****
	(.002)	*(.002)*	*(.003)*	*(.003)*
Lean Hogs	*0.001*	*0.002*	*0.005***	*0.004*
	(.002)	*(.002)*	*(.002)*	*(.003)*
Natural Gas	*0.006****	*0.012****	*0.009****	*0.014****
	(.002)	*(.002)*	*(.002)*	*(.003)*
NIKKEI 225 (OSE)	*0.005****	*0.011****	*0.013****	*0.008****
	(.002)	*(.002)*	*(.003)*	*(.003)*
NOK/USD	*0.005***	*0.001*	*0.002*	*-0.000*
	(.002)	*(.002)*	*(.003)*	*(.003)*
NASDAQ 100 mini	*0.008****	*0.007***	*-0.005*	*0.004*
	(.003)	*(.003)*	*(.004)*	*(.005)*
NZD/USD	*-0.006****	*0.000*	*-0.009****	*-0.000*
	(.002)	*(.002)*	*(.003)*	*(.003)*
Euro-OAT Future	*-0.001*	*0.009***	*-0.008***	*0.005*
	(.003)	*(.004)*	*(.004)*	*(.005)*
EURO-BOBL FUTURE	*0.014****	*0.019****	*0.040****	*0.031****
	(.002)	*(.003)*	*(.004)*	*(.004)*
Platinum	*0.006****	*-0.001*	*0.003*	*0.002*
	(.002)	*(.002)*	*(.003)*	*(.003)*
S&P/TSX 60	*0.002*	*0.006****	*-0.001*	*0.013****
	(.002)	*(.002)*	*(.003)*	*(.003)*
OMX STKH30	*0.008****	*0.020****	*0.005*	*0.009***
	(.002)	*(.003)*	*(.004)*	*(.004)*
Crude	*0.000*	*0.009****	*-0.000*	*0.009****
	(.002)	*(.002)*	*(.003)*	*(.003)*
EURO-BUND FUTURE	*-0.005****	*-0.008****	*-0.005**	*-0.019****
	(.002)	*(.002)*	*(.003)*	*(.003)*
Soybeans	*0.007****	*0.012****	*0.006***	*0.010****
	(.002)	*(.002)*	*(.003)*	*(.003)*
Sugar	*0.004***	*0.012****	*0.010****	*0.016****
	(.002)	*(.002)*	*(.002)*	*(.003)*
SEK/USD	*0.002*	*0.008****	*0.007***	*0.014****
	(.002)	*(.003)*	*(.003)*	*(.003)*
Silver	*0.005****	*0.006****	*-0.001*	*0.001*
	(.002)	*(.002)*	*(.003)*	*(.003)*
SWISS MKT	*0.006****	*0.006***	*0.005**	*0.003*
	(.002)	*(.002)*	*(.003)*	*(.003)*
Soybean meal	*0.001*	*0.001*	*0.002*	*-0.000*
	(.002)	*(.002)*	*(.003)*	*(.003)*
FTSE MIV	*0.009****	*-0.006***	*0.007**	*-0.005*
	(.003)	*(.003)*	*(.004)*	*(.005)*

US 2YR NOTE	*0.006***	*0.010****	*0.006**	*-0.005*
	(.002)	*(.003)*	*(.004)*	*(.004)*
US 10YR NOTE	*-0.002*	*0.003*	*0.014**	*-0.015*
	(.004)	*(.005)*	*(.008)*	*(.009)*
EURO-BUXL 30Y BND	*0.005***	*0.006****	*0.007***	*0.018****
	(.002)	*(.002)*	*(.003)*	*(.004)*
US LONG BOND	*0.006**	*0.016****	*0.011***	*0.001*
	(.003)	*(.003)*	*(.005)*	*(.007)*
US 10YR ULTRA FUT	*0.004*	*-0.006*	*-0.003*	*0.035****
	(.004)	*(.004)*	*(.005)*	*(.005)*
EURO STOXX 50	*-0.012****	*0.003*	*-0.008*	*0.007*
	(.004)	*(.005)*	*(.006)*	*(.007)*
Chicago Wheat	*0.003*	*0.006***	*0.007**	*0.002*
	(.002)	*(.003)*	*(.004)*	*(.004)*
US ULTRA BOND	*-0.004*	*0.007**	*0.011***	*0.011**
	(.003)	*(.004)*	*(.005)*	*(.006)*
Gasoline	*0.008****	*0.014****	*0.012****	*0.021****
	(.002)	*(.002)*	*(.003)*	*(.003)*
S&P/ASX	*0.012****	*0.008****	*0.010****	*0.003*
	(.002)	*(.002)*	*(.003)*	*(.003)*
FTSE 100	*0.006***	*0.011****	*0.001*	*0.003*
	(.002)	*(.003)*	*(.004)*	*(.004)*
R^2	*0.452*	*0.54*	*0.5*	*0.689*

TABLE C1: RETURN OF ALL INSTRUMENTS REGRESSED ON RETURNS OF MANAGE FUTURES INDICES

*Notes: The statistical significance is presented at the 10%, 5% and 1% levels using the asterisks *, ** and ***. Besides, standard errors are in the parentheses*