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A Sober Walk Down Wall Street

Risks and Benefits of a Trend Following Strategy

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Abstract

This thesis examines an investment strategy referred to as trend following. We construct a rule-based trading algorithm, built solely on past prices and volatility, aiming at capturing trends in futures markets. We explore whether standard theoretical risk factors and more recently presented momentum-related risk factors can explain the time-variation in trend following excess returns. A holistic perspective is also exerted, in which the impact of including a divergent component to a standard 60/40 portfolio (a portfolio that is 60% invested in equities and 40% invested in bonds) is examined. The strategy is tested against an investment universe comprising of 76 global and liquid futures contracts, to represent a real-life implementable strategy. Our results show a low explanatory power of standard theoretical risk factors and a statistically significant positive alpha, amounting to 0.9% on a monthly basis. This finding challenges the random walk hypothesis and shed new light on the often criticised field of technical analysis. We document a significant and positive relationship between the strategy and time series momentum. Despite this, the strategy generates a positive and significant alpha of 0.4% on a monthly basis above time series momentum. This implies that intuitive trading-rules based on past price movements are efficient tools that can be utilised to create alpha. The strategy also delivers a positive and significant alpha above the industry benchmark, suggesting that Commodity Trading Advisor (CTA) funds occasionally divert from their core principals, in favor of less successful strategies. Finally, we find evidence that the inclusion of a trend following component to a standard 60/40 portfolio can increase risk-adjusted returns, reduce left-tail risk and enhance the ability to recover following drawdowns.

Keywords: Trend following, time series momentum, divergent trading strategy, futures

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1 Introduction

In light of the recent Nobel Prize winners Fama, Hansen and Schiller, the financial industry is evidently divided with respect to the perception of underlying reasons for movements in asset prices (e.g. Authers 2013). To paint the picture black and white, there are advocates for a stable (efficient) world and there are advocates for a more irrational world where behavioral biases and heuristics have explanatory power in asset pricing. This polarisation lies close to the concept of a convergent and a divergent view of the world. In a convergent world a fair value exists and an equilibrium price can be determined. In a divergent world, markets are ever-changing and unstable in nature. A convergent trader aims to exploit temporary price discrepancies whereas the divergent trader recognizes that everything is dependent (Rzepczynski 1999). Trend following is a trading strategy subject to the latter of the two perspectives. This polarisation is not only present in academia, but also accentuated in the practitioners' side of the industry in which e.g. value-oriented funds, emphasising the long-term fundamental value, stand in stark contrast to CTA funds.

As brought forward in Cootner (1964) and later popularised by Malkiel (1973), future steps cannot be predicted on the basis of past actions. Metaphorically, scholars sometimes refer to this as a drunkard walking randomly, while trying to find his way home from the bar. Such reasoning of random walk behavior has been challenged in several contexts, e.g. recently by AQR[1] principals Moskowitz, Ooi and Pedersen (2012). They find significant positive auto-covariance in a number of different asset classes, suggesting a strong common component of intra-asset momentum, referred to as time series momentum. Although the academic literature with respect to momentum has grown steadily since the introduction of Carhart's four factor model (Carhart 1997), the current literature primarily relates to cross-sectional momentum. Cross-sectional momentum refers to the return of an asset in relation to the return of other assets, as opposed to in relation to its own past returns. The latter relationship has been more debated outside of academia and, as Lo, Mamaysky and Wang (2000) point out, it deserves to be further investigated. Especially in light of Moskowitz, Ooi and Pedersen's (2012) findings and the growing practitioner community of CTA funds and trend followers.

As a complement to recent discoveries we document the characteristics of a trend following strategy in an academic setting. The strategy is based on a straight-forward trading algorithm as described in Clenow (2013). By analysing back adjusted continuous price series for a global investment universe encompassing 76 futures contracts, received from the Swiss based hedge fund ACIES Asset Management, we are able to construct and evaluate a real-life implementable trend following strategy. By constructing

[1]AQR Capital Management is an active management London based hedge fund.

the trading strategy ourselves, we can provide a deeper understanding of the underlying factors, driving the characteristics of the strategy. Taking the results of such an analysis into an academic context is not only valuable for trend following practitioners, but also for bridging the gap between academia and the hedge fund industry.

We find that the trend following strategy carries low exposure to standard risk factors, such as the risk premia attributable to market, value, size and short and long-term reversals. The strategy is associated with a positive and statistically significant exposure to the time series momentum risk premia and a positive exposure to the squared term of the world equity index (used as a proxy for extreme events in the equity market). The strategy delivers positive and statistically significant alphas over the time series momentum risk factor as well as over its industry benchmark. The former alpha implies that more sophisticated trading rules can refine and add to the time series momentum risk premia whereas the latter alpha suggest that some CTA fund managers occasionally divert from trend following rules in order to reduce short-term volatility, with a poorer performance as the result.

The return distribution of the strategy is positively skewed, with a high number of small negative returns and a low number of large positive returns, making up for the small losses. Such return characteristics provide useful diversification benefits to a standard 60/40 portfolio by reducing the magnitude of left-tail events and downside volatility while simultaneously improving the ability to recover following drawdowns.

The remainder of the thesis is organized as follows. A summary of existing literature on momentum and trend following is presented in Section 2. Section 3 introduces the theoretical framework and the hypotheses tested. The data utilised in the analysis, along with the required adjustments are described in Section 4. Section 5 demonstrates the methodology and trading strategy implementation. Empirical findings are presented in Section 6, followed by Section 7 where tail events and implementability are discussed. In Section 8, robustness of the results are tested by performing a sensitivity analysis with respect to key input parameters used in the trading algorithm. Finally, our concluding remarks along with limitations and suggestions for further research are outlined in Section 9.

2 Literature Review

In this section a brief literature review is presented, aiming at summarising the existing literature with respect to market efficiency, cross-sectional momentum, time series momentum and trend following.

2.1 Market efficiency

The efficient market hypothesis was established by Fama (1970) and states that markets are informationally efficient if prices, at all time, reflect all available information. The hypothesis is closely linked to the concept of investor rationality and the random walk hypothesis; the competition among market participants to exploit any predictable pattern in prices will leave prices random and unpredictable. The main implication of the efficient market hypothesis is an inability for investors to consistently outperform the market. Active management will be a zero-sum game before transaction costs and when accounting for costs, a negative-sum game. Thus, the best approach is to passively hold the market portfolio.

In recent years the notion that markets are not fully efficient at all times has become more accepted (Ilmanen 2011). Besides predictable patterns in the stock market such as cross-sectional momentum (Daniel and Moskowitz 2011) and long-term reversals (DeBondt and Thaler 1985), the IT-bubble as well as the recent financial crisis pose a challenge to the efficient market hypothesis. The emerging discipline of behavioral finance raises critique against the hypothesis, arguing that investors are not fully rational, but subject to biases, heuristics and fears (Barberis and Thaler 2003). The adaptive market hypothesis, presented by Lo in 2005 reconciles the efficient market hypothesis with behavioral alternatives, applying the concepts of evolution, competition, adaption and natural selection to financial markets. Lo (2005) concludes that the primary objective of market participants is survival (profit and utility maximisation is secondary) and that the relationship between risk and reward will be unstable over time.

2.2 Momentum

2.2.1 Cross-sectional momentum

Momentum in the finance literature usually refers to cross-sectional momentum; the tendency for securities that outperformed their peers in the past to continue outperforming their peers in the future. E.g. Jegadeesh and Titman (1993, 2011) and Daniel and Moskowitz (2011) find that investors can achieve positive abnormal returns by buying stocks that have performed well in the past and selling stocks that have performed poorly. These findings are robust to various look-back and holding periods and apply to other asset classes than equities as well, e.g. country equity indices (Bhojraj and Swaminathan 2006), currencies (Schleifer and Summer 1990) and commodities (Erb and Harvey 2006).

Behavioral reasons put forward to explain this serial-correlation in prices are an initial underreaction to new information caused by a conservatism bias (Edwards 1968 and Mullainathan 2001), together with the disposition effect (Grinnblatt and Han 2005, Frazzini 2006), followed by a delayed overreaction caused by a representative heuristics (Kahneman, Slovic and Tversky 1974). The conservatism bias suggests that investors underweight new information when updating their prior beliefs while the disposition effect predicts that investors with loss-aversion tend to sell past winners while keeping past losers. Such behavior would be explained by the employment of the purchase price as an anchoring point, i.e. a reference point from which the performance is evaluated. The conservatism bias together with the disposition effect predict prices to slowly adjust to new information. The representative heuristic would result in a delayed overreaction to new information as individuals have a tendency to rank probabilities of outcomes in the dimension of how representative, rather than how likely, they are. In practice, such behavior may lead investors to conclude that stocks realising abnormal return in one period will continue to experience similar growth in the future. With regard to institutional investors, Grinblatt, Titman and Wermers (1995) find that mutual funds tend to buy and sell the same stocks at the same time, a behavior referred to as herding. A rational explanation for momentum returns is a positive loading on market-wide liquidity risk. Pastor and Stambaugh (2003) document that alpha stemming from a momentum strategy is significantly reduced when controlling for liquidity risk. Sadka (2006) also finds a positive relationship between momentum returns and liquidity, and concludes that momentum carries a compensation for liquidity risk.

2.2.2 Time series momentum

Instead of focusing on a security's relative return in the cross-section, time-series momentum focuses on a security's own past return. Moskowitz, Ooi and Pederen (2012) find a significant time series momentum effect across 58 futures markets, covering the underlying of several different asset classes. The authors decompose the expected returns stemming from cross-sectional momentum into three factors: auto-covariance, cross-covariance and dispersion in mean. The results indicate that the auto-covariance is the driving force behind cross-sectional momentum, together with a small positive effect attributable to the dispersion in mean. The effect associated with the cross-covariance is actually negative. As time series momentum only captures the auto-covariance components and the dispersion in mean, it will generate higher returns than cross-sectional momentum. Furthermore, the authors find that time series momentum experiences strong and consistent performance across a diverse set of asset classes, especially during periods of high volatility. It also shows low exposure to standard risk factors. The strong performance remains consistent across different markets and is highly correlated across different asset classes. The correlation between time series momentum returns is higher than the correlation among passive long positions in the same asset classes. This finding implies that there is a common component to time series momentum, not present in the underlying assets themselves. By evaluating hedgers and speculators net position in the futures contracts, the authors find that speculators take on larger positions in assets experiencing positive returns than in assets experiencing negative returns. The authors conclude that speculators are, on average, positioned to benefit from trends, whereas hedgers by definition take the opposite position. Thus, speculators profit from following trends, at the expense of hedgers. In this sense, they earn a time series momentum risk premia by providing liquidity to hedgers. Hence, the authors provide an alternative, structural, underlying explanation of why time series momentum exist in addition to behavioral explanations.

2.3 Trend following

Trend following is a more sophisticated approach for investors to try to benefit from time series momentum in asset prices. Vice versa, time series momentum can be though of as the simplest form of trend following. Trend following aims at identifying trends in price series and long assets that show a positive trend and short assets that show a negative trend (Clenow 2013). If the trend continues, the strategy will yield a positive return. Via futures contracts, the strategy can be implemented in a range of liquid asset classes. Asness, Moskowitz, and Pedersen (2013) conclude that benfits of investing in futures contracts include lower transaction costs compared to equities, symmetric conditions for long versus short positions as well as a high ability to diversify among different asset classes.

Hurst, Ooi and Pedersen (2012) evaluate trend following in a global setting over the last 110 years and find consistent high returns and low correlation to stocks and bonds. The strategy tends to do well in extreme bull or bear stock markets, exemplified most recently by its strong performance in the global financial crisis. The authors find significant evidence that trend following has performed well in a consistent manner over more than a century and conclude that trends in global markets is a robust phenomenon and not a statistical fluke. Reasons put forward to the existence of exploitable trends are behavioral biases such as anchoring and herding. Also, the existence of non-profit seeking agents such as hedgers can create trends, as presented in Moskowitz, Ooi and Pedersen (2012). Speculators may benefit from corporate hedging programs by being on the other side of the trade. When evaluating the performance of trend following in recent years, the strategy has experienced a bit of a drawback following the financial crisis. The authors argue that increased asset under management for trend following strategies is not the root cause of the problem since the futures market is still mainly occupied by hedgers; speculators constitute only a few percent of outstanding volumes. They instead argue that the recent drawdown is not outside of the normal range but that it could be driven by a temporary increase in correlation across markets following the financial crisis and hence, lower diversification of trends. Historically, the correlation has been high in sub-periods before returning to normal levels. In addition, an argument for future consistent performance of trend following is that the emerging markets are becoming more liquid, leading to a potential expansion of the investment universe and hence more diversification benefits.

Clenow (2013) creates a trend following strategy, *The break-out strategy*, and by altering the risk level and the time horizon of trades, he is able to closely replicate the performance of the largest CTA funds. The author finds a consistent performance of the strategy as well as a low correlation to overall equity markets. During 2008 when equity markets fell, the break-out strategy was able to achieve positive abnormal returns. With regards to the poor performance of trend following in recent years, Clenow argues that the financial markets of today are experiencing shorter cycles than before, partly driven by the increase in regulation (e.g. Basel III and Quantitative Easing) aiming at dampening business cycles. Together with a low-interest rate environment and increased correlation between asset classes, this is resulting in an unfavorable environment for trend following.

Koulajian and Czkwianianc (2010) propose two trend following strategies: *The 50 day channel break-out strategy* and *The 10x100 simple moving average cross-over strategy. The 50 day channel break-out strategy* is, in line with Clenow (2013), able to explain most of the returns of the trend-following index Barclay BTOP50[2]. The simple strategies proposed yield higher risk-adjusted returns than the trend-following index and the S&P 500 index. The returns stemming from the two strategies result in a positively skewed return distribution that tends to benefit from increased volatility and downward movements in the S&P 500 index. In addition, the negative correlation to the S&P 500 index has a tendency to increase in magnitude when the index experiences a drawdown. Over the last 20 years the main profit-drivers of the two strategies have been the fixed income and agricultural sector, long trades and longer term frequencies. Shifting a trend following strategy to benefit from these profit drivers could increase risk-adjusted returns in a low-volatility environment. Nevertheless, it will potentially dilute its value as a hedging instrument in equity drawdowns.

Koulajian and Czkwianianc (2013) evaluate the trend following index Barclay BTOP50 and its correlation to the The Dow Jones Credit Suisse Hedge Fund Index and the S&P 500 Index. The authors find evidence suggesting that CTA funds in recent years have reduced their exposure toward trend following. CTA funds have increased the time frames of their models, increased long biased trading and increased their exposure to fixed income trading. In the extension, this lead to a higher correlation to equities and other hedge fund strategies as well as a less positive skew of the return distribution.

[2]The BTOP50 Index seeks to replicate the overall composition of the managed futures industry with regard to trading style and overall market exposure.

2.4 Convergent versus divergent trading

Ching, Rosenberg and Tomeo (2004) dichotomise active trading into two different styles: convergent and divergent trading. A convergent asset manager is confident in the view that the world is stable, knowable and stationary. Divergent management, on the other hand, relies on the belief that markets are dynamic and ever-changing (Rzepczynski 1999). Although there may be some long-run stable relationships between fundamental information and prices, markets are experiencing constant structural change and the behavior is unknown in the short-run. Errors in markets and models are significant and long-lasting. Together with the exogenous model uncertainty, there is also endogenous uncertainty with respect to the behavior of market participants and processing of information. Investors make mistakes and create biased beliefs, this lead to a need for adjustments, learning and new equilibrium prices. Only part of the volatility observed in financial markets can be attributable to fundamental information. As markets adjust to new information and learn, trends are formed as a result of an initial under-reaction to new information (Hirshleifer and Subrahmanyam 1998). What Chung, Rosenberg and Tomeo (2004) find is that the correlation between the two trading styles is low and even negative in two out of four subsamples. Along with the low correlation, the different characteristics of return distribution enables diversification benefits to investors. By creating portfolios that combine the two strategies, the number of negative outliers is reduced and returns are enhanced compared to any of the stand-alone strategies. This implies a positive shift in the return distribution, i.e. an increased skew. While volatility indicates the degree to which a strategy's performance deviates from the average, skew indicates the direction of the volatility. Positive skew is hence associated with positive outliers and negative skew is associated with negative outliers (Koulajian and Czkwianianc 2010). Leland (1999) argues that investors do distinguish between downside risk and upside risk. He concludes that in the extension, this leads to investors having a preference for positive skewed returns and that alongside volatility, skew can add to a deeper understanding of the actual risk being present.[3] Ching, Rosenberg and Tomeo (2004) find the most efficient portfolio to be an 80/20 investment in a convergent/divergent strategy, resulting in a higher Sharpe- and Sortino ratio than any of the two strategies individually. The magnitude of the increase in the Sortino ratio is considerably higher than the increase in the Sharpe ratio, implying asymmetric risk characteristics of the divergent strategy

[3]With respect to expected utility theory, a preference for positive skewness implies a positive third derivative of an investor's utility function. An investor who increases his/her risky investments as wealth increases must have a positive third derivative (Pratt 1964 and Arrow 1963). This will happen when risk aversion is absolute in relation to the wealth level (i.e risk aversion is not effected by wealth level). In 1979 Kahneman and Tversky derived the prospect theory which, according to the authors, provide a psychologically more accurate description of decision making compared to the expected utility theory. Investors use transformed, rather than objective, probabilities by applying a weighting function. The weighting function's main effect is a tendency to overweight the tails of the distribution. This overweighting does not capture biased beliefs, but is a modeling device that captures the common preference for positively skewed return distributions, observed in financial markets (Barberis and Huang 2008).

which emphasise the diversification benefits of combining it with a convergent strategy.

Asness, Moskowitz and Pedersen (2013) identify a common factor structure in the return premia to value and momentum strategies across global asset classes. They argue that part of the negative correlation between the return premia of value and momentum could be driven by the opposite exposure to liquidity risk. Evaluating a momentum strategy, a value strategy and a 50/50 combination, the authors find that the combination is able to outperform the stand-alone strategies in the majority of asset classes and significantly outperform when considering a global investment in all asset classes. The correlation between the return premia to value and momentum is consistently negative and averages -0.49.

Hurst, Ooi and Pedersen (2012) construct a typical 60/40 portfolio and compare it to a portfolio that is 80 percent invested in the 60/40 portfolio and 20 percent invested in a time series momentum strategy. Over the last 110 years the later portfolio would have resulted in higher returns and lower volatility. During the ten worst equity drawdowns in the last 110 years the portfolio comprising of 20 percent invested in a time series momentum strategy yielded positive returns in all drawdowns except for the stock market crash of 1987.

3 Theoretical Framework and Hypotheses

This section presents the main hypothesis we aim to test and the three sub hypotheses to which it can be divided, along with the underlying theoretical framework upon which the hypotheses are based.

3.1 The random walk hypothesis

In the mid 1960's Cootner (1964) and Fama (1965) presented the corner stones of research with respect to the random behavior of stock prices. They built upon the controversial topic in academia and business that regards whether past prices can be used to make meaningful predictions of future price paths. As Fama (1965) points out, the random walk hypothesis is built upon the idea of independent successive price changes defined as:

$$P(x_t = x \,|\, x_{t-1}, x_{t-2}, ...) = P(x_t = x) \tag{1}$$

That is, the probability distribution for the change in price is independent of the sequence of price changes realised during the previous period. To find a perfectly independent time series in reality is unlikely and for practical purposes, a minimum level of dependence can be accepted. This dependence can be evaluated from different perspectives, e.g. from a statistical point of view and from an investors more practical point of view. From a statistical point of view, the price of a security may increase by ϵ every second day and decrease by ϵ every second day. Such dependence may be important from a statistical point of view but as long as ϵ is small enough, it is not valuable for investors since such price changes cannot be profitably exploited due to transaction costs. Hence, from the perspective of an investor, dependence in prices is only relevant if it can be used to increase expected profit. The latter type of independence is further criticised in Malkiel (1973) who contextualises and evaluate the hypothesis by arguing that one cannot consistently outperform the market, especially not after transaction costs have been deducted.

3.2 The adaptive market hypothesis

The adaptive market hypothesis aims at reconciling economic theories based upon the efficient market hypothesis by including elements of evolutionary principals such as competition, reproduction and natural selection (Lo 2005). Prices reflect as much information as dictated by the environmental conditions (e.g. level of liquidity, institutions, business cycles, regulation, taxes) as well as number and nature of species/investors (e.g. institutional investor, pension funds, hedgers) in the economy. If competition is high and resources scarce, markets are likely to be highly efficient. An example of such a highly competitive market is the 10-year US Treasury notes, characterised by a quick incorporation of new information into the price. Markets where a fewer number of species are present may be less efficient and provide significant arbitrage opportunities. Profit opportunities constitute the food and water in the ecology and if they are abundant, the population will increase. If they are scarce, species will die out and the population will decrease. Unsuccessful traders are eventually eliminated from the population if they suffer certain level of losses. The survival of the fittest is applied to financial markets and Lo (2005) denotes it survival of the richest. The hypothesis allows for bounded rationality, in line with Simon (1955), implying that humans are limited in their computational skills and engage in satisficing, rather than optimal, activities.

There are five main implications that can be derived from the adaptive market hypothesis. First, the relationship between reward and risk is likely to be unstable over time. The relationship is determined by relative sizes and preferences of the investors in the market, as well as institutional aspects such as regulations and taxes. Second, there will be arbitrage opportunities as markets are dynamic, including cycles, trends, bubbles and crashes. Species die out, others are born and business conditions change. These dynamics provide a motivation for active investing. From an evolutionary perspective, the existence of active financial management indicates that profit opportunities exist. Third, investment strategies will work well in some environments and poorly in others. Profit opportunities attributable to certain investment strategies may decline in profitability for some time, but might return as environmental conditions become more beneficial. An example is risk arbitrage, driven by merger and acquisition activity. Fourth, the primary objective is survival and the key to survival is innovation. As the relation between risk and reward varies over time, investors need to adapt to changing market conditions by evolving multiple capabilities. Fifth, perhaps most importantly, survival is the only objective that matters for market participants. Profit and utility maximisation are aspects to consider in the ecology/market, but they are of secondary importance.

3.2.1 Hedgers and speculators

The fifth implication of the adaptive market hypothesis relates to the hedging demand observed in futures markets (Hurst, Ooi and Pedersen 2012). Hedgers are not acting with an intention to optimise profit, but rather with the intention to survive by minimising the cost of hedging, which can be exploited. They find that hedgers make up for the largest part of the futures market whereas speculators make up only a few percent. According to implication number two, a low number of species active in the market imply a less efficient market with potential arbitrage opportunities. Thus, there exists a substantial hedging demand in futures markets which can create arbitrage opportunities. With this theoretical framework in mind, we define one main hypothesis which in turn can be divided into three sub hypotheses.

3.3 Hypotheses

Main hypothesis: Past prices and volatility provide information of when and where trends in futures markets can be captured and exploited, to earn high risk-adjusted returns and downside protection.

Sub hypothesis 1: Excess returns stemming from a trend following strategy is negatively associated with the market risk premia and carries low exposure to other standard risk factors without imposing any cost of negative alpha.

Sub hypothesis 2: The inclusion of a trend following component to a portfolio decreases left-tail risk and offers a high ability to recover following drawdowns.

Sub hypothesis 3: Technical trading-rules can be practically implemented to replicate and beat a comparable trend following benchmark net of fees.

4 Data

In the following section data and data sources are presented. The data constitutes futures contracts, exchange rates, asset pricing benchmarks and initial margin requirements. Furthermore, the procedure of constructing back adjusted continuous price series of futures contracts is described. The time period evaluated is January 1990 to September 2013.

4.1 Futures contracts

The primary data analysed in this thesis constitute continuous back adjusted price series of 76 futures contracts received from ACIES Asset Management, a Swiss based CTA fund. The investment universe is presented in Table 9 in Appendix. The data includes open, close, high and low, representing the closing price, the opening price, the highest price observed during the day and the lowest price observed during the day. In addition, the corresponding unadjusted price series for the contracts are retrieved from the Bloomberg Database (2014). The underlying assets of the futures contracts are divided into five sectors: Agricultural (23 contracts), currency (16 contracts), equity (11 contacts), non-agricultural (11 contracts) and rate (15 contracts). The 76 futures contracts have been chosen based upon their level of liquidity. Liquidity is proxied by open interest, defined as the number of open contracts that are currently held by market participants (Clenow 2013). A high liquidity in the contracts analysed is essential in order to avoid returns being contaminated by stale prices and also, to evaluate an implementable strategy at a reasonable investment amount.

4.1.1 Trading futures contracts

A futures contract is a legal agreement to buy or sell an asset at a specific date for a price agreed upon today (Clenow 2013). At the end of the contracts life, the buyer (seller) has an obligation to buy (sell) the underlying asset at a predetermined price. Unlike forwards contracts, futures contracts are standardised and facilitated through an exchange. The contracts have detailed specifications related to delivery, quantity and quality of the underlying asset. The price is established at the exchange trading floor or at an electronic futures exchange. The major advantage of trading futures contracts is the ability to, in a single coherent manner, invest in a number of different asset classes in order to make full use of diversification effects. Furthermore, as futures represents a zero sum game (someone is always short when someone else is long), there is no increased complexity or transaction costs associated with a short position.

The original idea behind futures contracts was hedging; it provides an ability to lock in a future price for the underlying asset today and thereby removing the risk of adverse price changes during the holding period. Still today, hedgers represent the majority of open interest in futures contracts and speculators make up for only a few percent (Moskowitz, Ooi and Pedersen 2012). Futures exchanges use mark-to-market accounting, meaning that gains and losses on positions are settled in cash at the end of every day. Compared to stock trading, trading with futures does not require an up-front payment of the full amount of the position at initiation. A trader, establishing a position through a futures contract, is only required to put up the initial margin. The initial margin is used to debit the day-to-day losses and usually comprises no more than 10% of the notional amount of the contract (Greyserman and Kaminski 2014). Depending on the volatility and type of the instrument as well as the market conditions, the initial margin can vary (lower for the less volatile contracts). The margin requirement is set by the exchange and may change at any time.

4.1.2 Limited time span and back adjustments

Since futures contract have a date of expiry, agents that do not wish to participate in a transaction of the underlying asset but maintain their exposure will offset their current positions and take a new position. This process is referred to as the "roll over". Due to the cost of carry, c (measuring the interest cost - income earned + storage costs), and convenience yield, y (measuring benefits from owning the underlying asset), futures prices, F, on contracts with the same underlying, S, but with different maturities, T, can trade for different prices in the market (Hull 2013).

$$F_t = S_t \times e^{(c-y)(T-t)} \tag{2}$$

If futures contracts with shorter time to maturity have a lower price than contracts with a longer time to maturity, the term-structure is upward sloping and said to be in contango. That is, the price of the contract is higher than the spot price. This will happen when the cost of carry exceeds the convenience yield. If contracts with short time to maturity have a higher price than contracts with a longer time to maturity, the term-structure is downward sloping and said to be in backwardation. Thus, the price of the contract is lower than the spot price. This will happen when the convenience yield exceeds the cost of carry.

Due to the limited life span of future contracts, a number of different contracts must be linked together in order to create a continuous time series of prices. Henceforth, a futures contract will refer to the linked series of individual contracts forming a continuous time series of prices. The first step is to identify the most liquid contract. This may be the contract with the closest time to maturity, but this is not certain and it is also highly unpredictable when another contract becomes more liquid. Therefore, the definition of liquidity applied in this thesis is based on open interest. Thus, the strategy is always invested in the contract with the highest level of open interest. The second step is to link the contracts together. For unadjusted price series, the prices are simply put after each other. However, due to the difference in prices for contracts with different maturities, negative or positive gaps exist when you switch (roll over) between contracts with different maturities. Such gaps need to be removed in order to end up with a continuous time series that properly reflects the market movements. The back adjustment is performed by linking the contracts together so that the old contracts closing price matches the new contracts closing price on the roll over date. This means that the time series back in time will be shifted up or down (depending on the term structure) to match the new series. The last price of the time series will always be correct (the same as the price quoted in the market) but previous adjusted prices may have a mismatch with the actual price at a given point in time. For a graphical illustration of the adjustment, readers are referred to Figure 4 in Appendix.

4.2 Exchange rates

The price series for the futures contract are denominated in their local currencies. In order to translate the profit and loss into US Dollars (hereafter denoted USD), the daily closing exchange rates for the evaluated time period are retrieved from Datastream (2014).

4.3 Asset pricing benchmarks

The Morgan Stanley Capital World Index ($MSCI$), the 6 months London Interbank Offered Rate ($6mLIBOR$), the Barclays Capital Aggregated Bond Index ($BCBI$) and the Goldman Sachs Commodity Index ($GSCI$) are obtained from Datastream (2014). $MSCI$ is applied as a proxy for the world equity market. The index includes over 1000 stocks from 23 developed countries and represents a commonly employed benchmark. $6mLIBOR$ represents the interest rate at which banks can borrow from other banks in the London interbank market. The rate is compounded on a semi-annual basis and fixed on a daily basis by the British Bankers' Association. $BCBI$ is employed as a proxy for the bond market. The index is maintained by Barclays Capital and represents investment grade bonds traded in the US. As a proxy for the commodity market, $GSCI$ is applied. The index is world-production weighted and includes the most liquid commodity futures. It is maintained by Standard & Poor.

Finally, the performance benchmark Credit Suisse Managed Futures Index (*CS Man Fut*) is attained from the Credit Suisse Hedge Fund Index webpage (2014). The Credit Suisse Hedge Fund Indices are compiled by Credit Suisse Hedge Index LCC. *CS Man Fut* measures the aggregated performance of the largest managed futures funds that employ systematic trading programs relying on historical price data and market trends. Performance data used in the *CS Man Fut* is net of fees.

4.4 Theoretical risk factors

The long-short risk factors *MKT-Rf*, *SMB*, *HML*, *UMD*, *STR* and *LTR* are obtained from Kenneth R. French's web page (2014), representing market, size, value, cross-sectional momentum, short-term reversal and long-term reversal risk premias in global equities. In addition, the Fama French proxy for the risk free rate, Rf, is downloaded from the same web page. The long-short risk factors value and cross-sectional momentum across asset classes, *VAL EV* and *MOM EV*, as well as the long-short time series momentum factor, *TS MOM*, representing the risk premia associated with time series momentum in stocks, equity-indices, currencies, bonds and commodities are retrieved from Lasse H. Pedersens web page (2014).

MKT-Rf measures the return of the market above the risk free rate, *SMB* measures the return of small firms above big firms and *HML* measures the return of high book-to-market stocks (value stocks) above low book-to-market stocks (growth stocks). In order to construct the *SMB* and *HML* factors, six value-weighted portfolios, formed on size and book-to-market, are constructed. The stocks included are ranked based on size (market capitalisation) and the median is then used to split the sample into two groups, small and big. The stocks are also divided into three book-to-market groups, based on the breakpoints for the bottom 30% (low), middle 40% (medium) and top 30% (high) of the ranked values of BE/ME (obtained by dividing the book equity by the market equity). The *SMB* factor measures the average return of the three small portfolios minus the average return of the three big portfolios whereas the *HML* factor displays the average return of the two value portfolios minus the average return of the two growth portfolios. The *MKT-Rf*, *SMB* and *HML* factors employ a twelve months evaluation and holding period. For further information on how the market, size and value factors are constructed, see Fama and French (1993).

UMD measures the excess return of "up-stocks" above "down-stocks". The factor is constructed from six value-weighted portfolios formed on size and prior returns. The factor shows the average return of two (big and small) high prior return portfolios (above 70th percentile) minus the average of the two low prior return portfolios (below the 30th percentile). Prior return is measured in month t-12 to t-2 and the holding period is one month. For more detailed information about the factor, see Carhart (1997).

The *STR* is constructed in a similar manner as the *UMD* factor. Six value-weigthed portfolios are formed on size and prior returns. The factor displays the average return of the two low prior return portfolios minus the average of the two high prior return portfolios. Prior return is measured in month t-1 and the factor's holding period is one month. For more information about short-term reversals, see Jegadeesh (1990). The *LTR* factor is constructed using the same approach, the only difference is that the evaluation period is month t-60 to t-13. For further information about the long-term reversal factor, see De Bondt and Thaler (1985).

The *VAL EV* and *MOM EV* is constructed in a similar way as the *HML* and *UMD* factors. The difference being that the two latter factors do not only include stocks but also equity indices, currencies, bonds and commodity futures. In addition, Asness, Moskowitz and Pedersen (2013) define value somewhat differently than Fama and French. To ensure data availability to investors, book values are lagged six months while the most recent market values are used to compute the book-to-market ratio. Fama and French employ contemporary book values. For more detailed information, see Asness, Moskowitz and Pedersen (2013). *TS MOM* is constructed using futures contracts covering equities, currencies, commodities and fixed income. Following the construction of the *UMD* factor, the factor is based on performance in month t-12 to t-2 and the holding period is one month. A positive (negative) return in the evaluation period results in a long (short) position in the coming month. The positions are scaled such that they have equal ex-ante volatility. For more information on the time series momentum factor, see Moskowitz, Ooi and Pedersen (2012).

4.5 Initial margin requirements

In order to assess the implementability of the trend following strategy and the reasonability of our assumptions, a sample of initial margin requirements during the year of 2008 is obtained from the Chicago Mercentile Exchange (CME) Group. As the availability of initial margin data is scarce one contract from each sector has been chosen for representation.[4] The underlying asset of the representative futures contracts chosen are: Corn (agricultural sector), Australian dollar (currency sector), Nikkei 225 (equity sector) and Eurodollar (rate sector).

[4] Historical initial margin requirements for the fifth sector (non-agricultural) are not available. CME group does not have data on historical margins for the non-agricultural sector prior to 2009 when they acquired NYMEX.

5 Methodology

At the heart of the concept of trend following lies a set of trading-rules, designed to capture trends in the market. In this section, an example of such rules is introduced to the readers. A legitimate concern is that the set of parameters chosen to create a trend following strategy are fitted to show the desired results. To address such concerns, robustness of main results is tested by altering the inputs of several critical parameters in Section 8. The focus of this section is the concept of capturing trends rather than the exact choice of input parameters.

5.1 Trading strategy implementation

The break-out strategy, proposed in Clenow (2013), aims at exploring mid-term trends in the market by taking symmetric long and short positions in futures contracts. The strategy consists of five central components: Entry rule, trend filter, exit rule, position sizing, and a stop/loss mechanism.

5.1.1 Entry rule

If today's closing price is equal to, or higher (lower) than, the highest (lowest) closing price in the preceding 50 days, a long (short) position is established. The position is implemented in the following trading day assuming execution at the closing price.

$$close_{t,j} \geq max\ (close_{t-50,j} : close_{t,j}) \rightarrow entry\,^{long}_{t+1,j} = true \tag{3}$$

$$close_{t,j} \leq min\ (close_{t-50,j} : close_{t,j}) \rightarrow entry\,^{short}_{t+1,j} = true \tag{4}$$

Where *close* represents the back adjusted closing price denoted in USD, *min* is short for minimum, *max* is short for maximum, t represents time measured in trading days, and j represents the specific futures contract (e.g. gold or sugar).

5.1.2 Trend filter

A problem with the break-out strategy is that it has a tendency to, in some periods, go against the main trend in the market. E.g. if the market has experienced an upward moving trend, a brief reversal of the prevailing up-trend is not unusual. Such a pause in the upward momentum may create a false entry signal for a short position. To avoid this problem, the entry criteria is extended to also include a trend filter. A long (short) position is entered only if the moving average (hereafter denoted MA) for the last 50 days closing price is higher (lower) than the moving average for the last 100 days closing price.

$$MA_{50}\left(close_{t,j}\right) = \sum_{\tau=t-50}^{t} close_{\tau,j}/50 \tag{5}$$

$$MA_{100}\left(close_{t,j}\right) = \sum_{\tau=t-100}^{t} close_{\tau,j}/100 \tag{6}$$

$$MA_{50}\left(close_{t,j}\right) > MA_{100}\left(close_{t,j}\right) \rightarrow trend\,_{t,j}^{up} = true \tag{7}$$

$$MA_{50}\left(close_{t,j}\right) < MA_{100}\left(close_{t,j}\right) \rightarrow trend\,_{t,j}^{down} = true \tag{8}$$

5.1.3 Exit rule

A long (short) positions is sold (covered) when the closing price is equal to, or less (higher) than, the lowest (highest) closing price in the preceding 25 days. Again, the trade is implemented at the closing price on the trading day following the received signal.

$$close_{t,j} \leq min\left(close_{t-25,j} : close_{t,j}\right) \rightarrow exit\,_{t+1,j}^{long} = true \tag{9}$$

$$close_{t,j} \geq max\left(close_{t-25,j} : close_{t,j}\right) \rightarrow exit\,_{t+1,j}^{short} = true \tag{10}$$

5.1.4 Position sizing

In order to maximise the utilisation of diversification, each position is computed to have the same theoretical profit/loss impact per day on the overall strategy. Thus, positions in less volatile futures contracts are going to be larger and positions in more volatile contracts are going to be smaller. The volatility measure employed is the average true range (hereafter denoted *ATR*), measuring the average of the true range (hereafter denoted *TR*), i.e. the price span in which a contract is traded for in a given day.

$$TR_{t,j} = max\left(high_{t,j},\ close_{t-1,j}\right) - min\left(low_{t,j},\ close_{t-1,j}\right) \tag{11}$$

Where *high* (*low*) represents the highest (lowest) back adjusted price observed during the day. To arrive at the ATR, the 100 days exponentially weighted moving average of the *TR* is computed.

$$ATR_{t,j} = \frac{(100-1) \times ATR_{t-1,j} + TR_{t,j}}{100} \tag{12}$$

The ATR provides an expectation of how large movements in prices are on a regular trading day. Remaining aspects to consider are *risk*, *equity* and *point value*. *Risk* determines the theoretical daily impact of each position on the overall portfolio value. It can be scaled up or down depending on the level of risk aversion of the specific investor. A risk input of e.g. 10 basis points implies that a single futures contract can have a maximum theoretical impact of 10 basis points on the overall portfolio value per day. Since the investment universe is limited to 76 futures contracts, aggregated theoretical impact at any given day would be 7.6% in such a scenario. Nevertheless, volatility is time-varying and the impact could potentially be larger if volatilities of the contracts increase during the holding period. *Equity* refers to the value of the portfolio being traded. The initial portfolio value is set at 100 million USD, so as to ensure that positions in futures contracts with high point values will be entered. *Point value* is the size of the futures contract, reflecting the number of units included in one contract. As an example, one gold futures contract constitutes 100 ounces of gold and daily prices are quoted in USD per ounce.

$$\#\ contracts_{i,j} = \frac{risk \times equity_{t_0}}{ATR_{t_0,j} \times point\ value_j} \tag{13}$$

Where i represents the individual trade and t_0 represents the time the trade is initiated. The nominator of the above equation reflects the theoretical daily impact each position is restricted to comprise and the denominator represents the normal daily price move of a particular futures contract. Note that it is not possible to buy a fraction of a contract and that the ratio is rounded downward in such a case. The position entered is assumed to be held constant until the time of the exit.

5.1.5 Stop/loss mechanism

Before an exit signal is obtained, the magnitude of a potential loss can vary considerably. Thus, to avoid big losses, a stop/loss mechanism is imposed. Such a mechanism forces a netting of the position if the loss exceeds a predetermined threshold. If the difference between today's closing price and the best price since the initiation of the position exceeds three ATR units, the position is cancelled. This rule limits the potential loss to a maximum of three ATR units plus trading costs. Thus, for a long (short) position, the stop/loss mechanism is activated if today's closing price is three ATR units below (above) the highest (lowest) closing price since the position was entered. Again, the trading rule is implemented on the following trading day assuming execution at closing price.

$$max\ (close_{t_0:t,j}) - close_{t,j} > 3 \times ATR_{t,j} \rightarrow stop/loss\ {}^{long}_{t+1,j} = true \tag{14}$$

$$close_{t,j} - min\ (close_{t_0:t,j}) > 3 \times ATR_{t,j} \rightarrow stop/loss\ {}^{short}_{t+1,j} = true \tag{15}$$

For a graphical explanation of the applied trading-rules, readers are referred to Figure 5 in Appendix.

5.2 Exposure and margin to equity

The exposure in each time period is computed by multiplying the number of contracts the strategy is currently invested in (long and short) with the size of the contract and the unadjusted closing price of the contract. For the exposure calculation, the unadjusted closing price is used (instead of the back adjusted price) as it reflects the price quoted in the market at the time.

$$exposure_t = \sum_{j=1}^{76} (\#\ contracts_{t,j} \times point\ value_j \times close^{unadj}_{t,j}) \tag{16}$$

The collateral required by the exchange as initial margin when entering a position (henceforth referred to as margin) is obtained by multiplying the exposure with the initial margin requirement of the individual futures contract. As data on historical margin levels is scarce we follow Greyserman and Kaminski's (2014) assumption of a 1% (10%) initial margin requirement applied to the exposure of the rate (agricultural, currency, equity, non-agricultural) sector. That is, we assume that the broker requires investors to put up with 1% (10%) of collateral for taking on positions in a contract in the rate (agricultural, currency, equity, non-agricultural) sector. As highlighted in Table 13 in Appendix this assumption is in line with actual initial margin requirements.

$$margin_t = \sum_{j=1}^{76} (exposure_{t,j} \times initial\ margin\ requirement_j) \tag{17}$$

Lastly, the margin to equity ratio is obtained by dividing the margin by the total portfolio value.

$$margin\ to\ equity_t = \frac{margin_t}{equity_t} \tag{18}$$

The margin to equity ratio measures the amount of the total portfolio that is being held as margin at any particular time. It can be seen as an estimate of the amount of leverage being used (Greyserman and Kaminski 2014). Hurst, Ooi and Pedersen (2012) apply a margin to equity between 5 to 20% in the construction of the time series momentum factor and argue this is feasible for a real-life portfolio. With this argument in mind we adjust the *risk* input such that the average margin to equity for the strategy becomes 12% for the evaluated time period. This results in a *risk* input equal to 7.5 basis points. The 12% figure is reasonable with respect to Hurst, Ooi and Pedersen (2012) and even more importantly, in accordance with major CTA funds. E.g. two of the Credit Suisse Managed Futures Index constitutions, Lynx Asset Management AB and Superfund Green GOLD SPC employ an average margin to equity of 14% and 20% respectively (IASG 2014).

The remaining capital in the trend following portfolio, not posted at the exchange, is required to ensure liquidity in case the prices of the contracts move in an unfavorable way or the exchange raises the initial margin requirements due to increased volatility. As futures contracts are associated with mark-to-market accounting and the price movements are settled in cash at the end of every day, liquidity management is essential for this strategy. If there is not enough capital available to cover potential losses, the positions will be forced to be liquidated. Thus, the remaining capital, not posted at the exchange to cover margin requirements, is invested in the 6 months LIBOR.

5.3 Return computation and trading costs

The profit/loss per trade is calculated by multiplying the change in price during the holding period with the size of the contract (point value) and the number of contracts the strategy is invested in. In order to take into account slippage costs, i.e. costs of crossing the midpoint of the bid/ask spread, it is assumed that the round-trip slippage cost per contract per trade is 20 USD. Although this is a simplification it is a conservative estimate in line with the procedure outlined in Clenow (2013).

$$profit/loss_{i,j} = \big((close_{t_1,j} - close_{t_0,j}) \times \#\ contracts_{i,j} \times point\ value_j\big) -\ 20\ USD \times \#\ contracts_{i,j} \tag{19}$$

Where t_0 represents the time the trade was initiated and t_1 represents the time the trade was terminated. To arrive at the return per trade, the profit/loss associated with each trade is divided by the total portfolio value at the initiation of the trade.

$$return_{i,j} = \frac{profit/loss_{i,j}}{equity_{t_0}} \tag{20}$$

The return per time period is calculated by summing the profit/loss per trade in the time period, adding the profit stemming from the investment in the 6 months LIBOR and dividing it by the total portfolio value at the beginning of the evaluated time period.

$$return_{t-1:t} = \frac{\sum_{i=1}^{n}\sum_{j=1}^{76}(profit/loss_{i,j}) + \sum_{\tau=t-1}^{t}(equity_{\tau} \times (1 - margin\ to\ equity_{\tau}) \times 6mLIBOR_{\tau})}{equity_{t-1}} \quad (21)$$

Where *t-1* represents the beginning of the evaluated time period, t represents the end of the period, n represents the number of active trades in the period, $equity_{\tau} \times (1 - margin\ to\ equity_{\tau})$ represents the capital invested in the 6 month LIBOR and $6mLIBOR_{\tau}$ represents the return of investing in the 6 month LIBOR.

6 Empirical Findings

The empirical findings, obtained by analysing the data according to the methods outlined in the previous section, are in this section presented and analysed in four steps. First, the trend following trade statistics and performance is evaluated, providing an intuition of where the sources of return stems from. Second, the alpha and factor loadings with respect to theoretical risk factors and major asset classes are analysed. Third, the trend following strategy's performance in relation to its industry benchmark is assessed. Finally, the diversification potential of adding a trend following component to a portfolio is examined.

6.1 Trading statistics and trend following performance

Table 1
Trend following strategy trade statistics

Summary statistics per trade of the trend following strategy. The investment universe consists of 76 global futures contracts and the trading rules applied correspond to the break-out strategy. Return is based on total portfolio value and is net of trading costs. Long (short) leg represents the trades with a long (short) position in the futures contracts and sector represents that of the underlying asset. Volatility represents standard deviation and absolute kurtosis is reported. Holding period presents average holding period and is measured in trading days. The win/loss ratio is the number of trades with positive return in relation to number of trades with negative return. The sample period runs from January 1990 to September 2013 (6567 observations).

	Mean	Median	Volatility	Minimum	Maximum	Skewness	Kurtosis
Complete Strategy	0.037%	-0.061%	0.352%	-0.887%	3.712%	2.140	11.269
Long leg	0.057%	-0.055%	0.386%	-0.887%	3.712%	2.080	10.502
Short leg	0.012%	-0.069%	0.302%	-0.684%	2.799%	2.032	10.866
Sector							
Agricultural	0.043%	-0.064%	0.367%	-0.652%	3.712%	2.673	15.628
Currency	0.035%	-0.051%	0.337%	-0.766%	1.516%	1.364	5.778
Equity	0.023%	-0.068%	0.315%	-0.886%	1.651%	1.674	6.812
Non-agricultural	0.032%	-0.063%	0.346%	-0.735%	2.615%	2.157	11.235
Rate	0.049%	-0.058%	0.381%	-0.886%	2.419%	1.780	7.670

	# trades	Holding period	Win/loss
Complete strategy	6567	26.124	0.696
Long leg	3686	26.208	0.734
Short leg	2881	25.102	0.649
Sector			
Agricultural	2004	26.898	0.705
Currency	971	26.972	0.778
Equity	1159	24.826	0.612
Non-agricultural	1012	27.264	0.681
Rate	595	23.563	0.696

Table 1 presents summary statistics of return per trade, as well as number of trades, average holding period and win/loss ratio for the sample period January 1990 to September 2013. The statistics are displayed for the complete strategy, for the long and short leg (representing long versus short positions in the futures contracts) and for the five different sectors of the underlying assets. The complete strategy yields an average return per trade of 0.04%, median return of -0.06%, standard deviation of 0.35%, minimum return of negative 0.89% and maximum return of 3.71%. With regards to higher moments of the return distribution, the skew is 2.14 and the kurtosis is 11.27. The complete strategy results in 6567 trades with an average holding period of 26.12 days. The win/loss ratio, measuring the numbers of trades with positive return in relation to the number of trades with negative returns, equals 0.70. These findings are in line with Clenow (2013), who finds a positively skewed return per trade distribution and an average holding period of approximately six weeks. Moreover, a holding period of, on average, 26.12 days lies close to the one month holding period employed in Moskowitz, Ooi and Pedersen (2012).

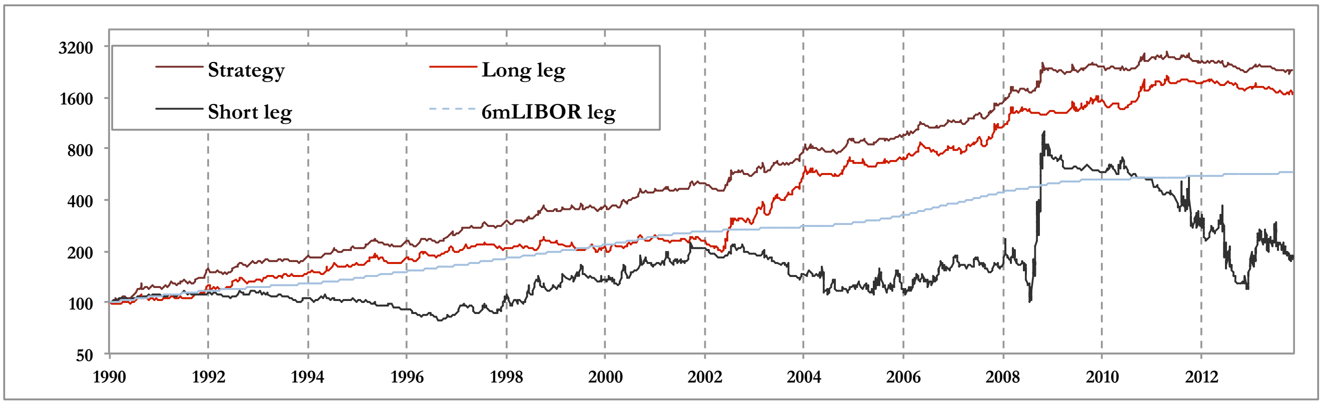
When analysing the trading statistics for the long versus the short leg of the strategy, the results show that both legs contribute positively to the strategy's return. Nevertheless, the long leg of the strategy is associated with a considerably higher average return. The median return remains negative, displaying a somewhat less negative median for the long leg. Furthermore, the long leg experiences a more extreme minimum and maximum return, a slightly higher skew and lower kurtosis, a higher number of trades, somewhat longer average holding period and a higher win/loss ratio, compared to the short leg.

To further analyse the profit driving components of the strategy, the summary statistics per trade are presented per sector of the underlying asset. All sectors show positive average return per trade; the highest (lowest) return is observed in the rate (equity) sector. The median return for all of the sectors is negative. The rate (equity) sector is associated with the highest (lowest) standard deviation and the lowest minimum (highest maximum) return is observed in the equity (agricultural) sector. All sectors show positively skewed return distributions with excess kurtosis. The agricultural (rate) sector represents the sector with the largest (lowest) number of trades and the non-agricultural (rate) sector represents the sector with the longest (shortest) average holding period. The win/loss ratio is highest (lowest) in the currency (equity) sector. Still, the ratio remains below one for all sectors, confirming that there are a few trades with high positive return that raise the average return per trade.

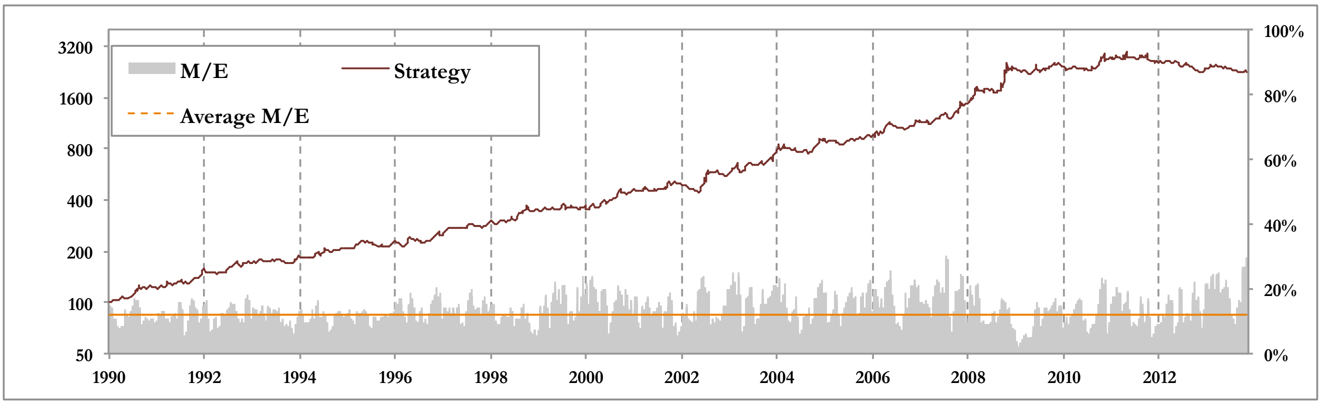
Figure 1
Cumulative return indices for the trend following strategy

Subfigure (a) plots the cumulative return indices based on the trend following strategy's daily return. The y-axis shows the cumulative index with a base of 100, where the scale is logarithmic. The investment universe consists of 76 global futures contracts and the trading rules applied correspond to the break-out strategy. Return is based on total portfolio value and is net of trading costs. Long (short) leg represents the long (short) positions in the futures contract and the 6mLIBOR leg represents the investment in the 6 months LIBOR. The sample period runs from January 1990 to September 2013 (6209 observations). Subfigure (b) plots the cumulative return index for the complete strategy on the primary y-axis. On the secondary y-axis, the margin to equity (M/E) along with the average M/E over the evaluated time period is displayed. Subfigure (c) plots return indices for the sectors of the underlying assets: agricultural (23 contracts), currency (11 contracts), equity (16 contracts), non-agricultural (11 contracts) and rate (15 contracts).

(a) *Cumulative return indices for the trend following strategy*



(b) *Cumulative return index and margin to equity*



(c) *Cumulative return indices for the five sectors of the underlying assets*

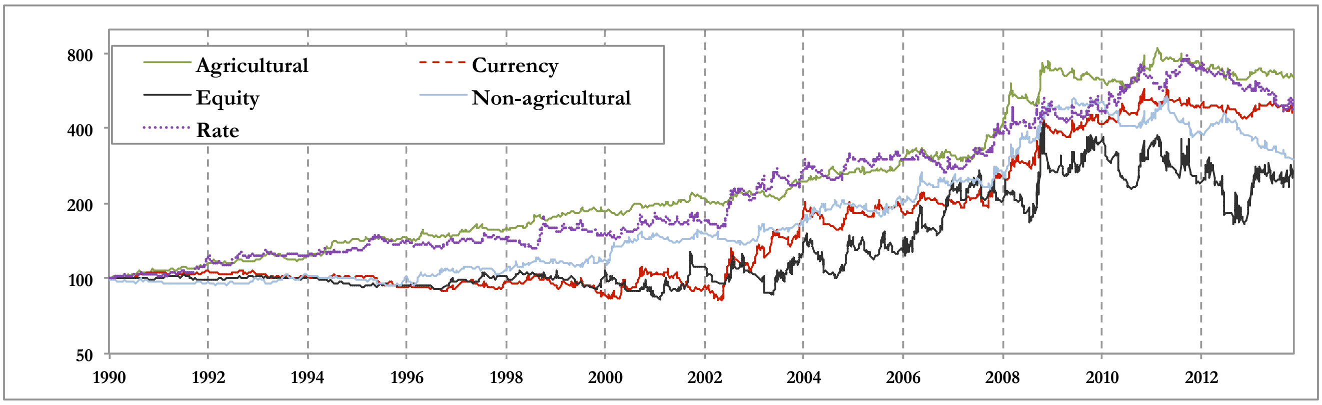


Figure 1a plots the cumulative return indices for the complete strategy, for the long leg, for the short leg and for the 6mLIBOR leg. The 6mLIBOR leg represents the return stemming from the capital that is not required for covering margin requirements and hence, is invested in the 6 months LIBOR. The long leg is the main profit driver of the complete strategy's return. Nevertheless, the short leg and the 6mLIBOR leg is contributing positively to the overall performance. Noticeable is a high return of the strategy in 2008 (see Table 10 in Appendix for yearly performance), mainly driven by the short leg. The strategy yields lower return in recent years, following the financial crisis, due to horizontal movements of the market and low trendiness. The long leg performs well in the years 2003 and 2007, indicating upward moving trends in the underlying markets. The short leg, on the other hand, performs well during 2000, 2001 and 2008 (throughout the IT-bubble and the financial crisis). Although the short leg displays negative returns in many years, it still provides benefits as it tends to perform well in crises periods. These findings are in accordance with Hurst, Ooi and Pedersen (2012) and Clenow (2013), that observe superior performance of trend following in the recent financial crisis, although equipped with somewhat lower returns in recent years.

Figure 1b plots the cumulative return index for the complete strategy on the primary y-axis. On the secondary y-axis, the margin to equity is plotted, along with the average margin to equity over the evaluated time period. The time-varying component behind the margin to equity is the number of contracts the strategy is invested in. This in turn is determined by the risk parameter, current equity value, point value and ATR (recall equation 13 in Section 5). Hence, a higher ATR will result in smaller positions and thus, lower margin to equity. This is highlighted in year 2008 when margin to equity is fairly low due to high volatility in the underlying markets.

Figure 1c displays the performance of the different sectors of the underlying assets over the evaluated time period. The agricultural sector, followed by the rate sector, are the best performing sectors, showing consistent positive returns over the evaluated time period. The equity sector is the worst performing sector. Noticeable is the strong performance in the agricultural and non-agricultural sectors during the financial crisis.

Table 2
Trend following strategy monthly returns

Summary statistics per month of the trend following strategy. The investment universe consists of 76 global futures contracts and the trading rules applied correspond to the break-out strategy. Return is calculated based on total portfolio value and is net of trading costs. Long (short) leg represents the trades with a long (short) position in the futures contracts and sector represents that of the underlying asset. Volatility represents standard deviation and absolute kurtosis is reported. The win/loss ratio is the number of months with positive return in relation to number of months with negative return. The sample period runs from January 1990 to September 2013 (285 observations).

	Mean	Median	Volatility	Minimum	Maximum	Skewness	Kurtosis
Strategy	1.178%	0.900%	4.057%	-9.617%	22.937%	0.899	5.966
Long leg	0.737%	0.403%	3.298%	-7.477%	17.153%	0.957	5.625
Short leg	0.126%	-0.092%	2.416%	-8.143%	23.206%	3.322	32.610
Sector							
Agricultural	0.305%	0.150%	1.377%	-3.099%	9.374%	1.710	10.965
Currency	0.123%	-0.002%	1.053%	-2.146%	5.288%	1.266	6.414
Equity	0.065%	-0.027%	1.151%	-3.195%	4.519%	0.787	5.287
Non-agricultural	0.116%	0.009%	1.038%	-2.686%	4.661%	0.815	5.823
Rate	0.254%	0.036%	1.605%	-3.586%	8.874%	1.369	6.756

	Win/loss
Complete strategy	1.453
Long leg	1.225
Short leg	0.901
Sector	
Agricultural	1.242
Currency	1.007
Equity	0.979
Non-agricultral	1.050
Rate	1.095

Table 2 provides summary statistics of the monthly returns for the trend following strategy during the sample period January 1990 to September 2013. Again, the statistics are presented for the complete strategy, for the long leg, for the short leg and for the five different sectors of the underlying assets. The complete strategy results in a monthly average return of 1.18%, median return of 0.90%, standard deviation of 4.06%, minimum return of negative 9.62%, maximum return of 22.94%, skew of 0.90 and kurtosis of 5.97. For the evaluated time period, the strategy results in a win/loss ratio of 1.45. Hence, the win/loss ratio is below one when assessing individual trades but above one when assessing monthly returns. This indicates that there are a few large trades each month that make up for many of the smaller losses, resulting in a larger number of positive months than negative ones.

Evaluating the long and short leg of the strategy, the average return per month is positive for both legs, but higher for the long leg. The median return is lower than the average return and even negative for the short leg. Standard deviation is slightly higher for the long leg. The short leg experiences a more extreme maximum and minimum return. This results in a lower skew and lower kurtosis for the return distribution of the long leg. Nevertheless, the return distribution of the long and short leg are positively skewed with excess kurtosis. The long leg yields a win/loss ratio of 1.23, suggesting that the long leg is associated with a higher number of months with positive return than months with negative return. The short leg yields a win/loss ratio of 0.90, implying that the opposite relation holds for the short leg.

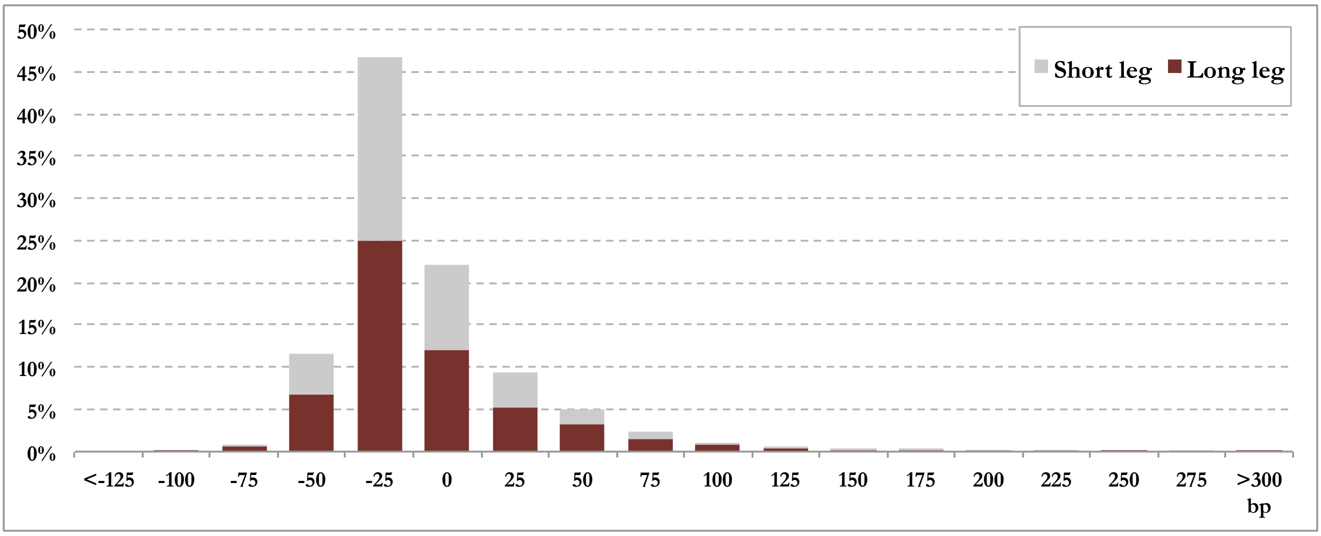
Assessing the monthly return for the five different sectors of the underlying assets, all sectors have a positive average monthly return. The agricultural sector represents the sector with the highest return, while the lowest return is attributable to the equity sector. The same pattern holds for the median return. The rate (non-agricultural) sector is associated with the highest (lowest) standard deviation and the rate (agricultural) sector shows the most extreme minimum (maximum) return. All sectors display positive skew and excess kurtosis. All sectors, except the equity sector, display a monthly win/loss ratio above one.

6.1.1 Return profile

Figure 2
Trend following return profile

Subfigure (a) shows return per trade distribution for the trend following strategy. The investment universe consists of 76 global futures contracts and the trading rules applied correspond to the break-out strategy. Return is based on total portfolio value and is net of trading costs. Long (short) leg represents the long (short) positions in the futures contracts. The x-axis represents the magnitude of the return quoted in basis points. The y-axis presents the percent of the distribution applicable to a certain return interval. The sample period runs from January 1990 to September 2013 (6567 observations). Subfigure (b) shows the monthly return distribution for the trend following strategy. The x-axis represents the magnitude of the return quoted in percent. The y-axis is the percent of the distribution applicable to a certain return interval. The sample period runs from January 1990 to September 2013 (285 observations).

(a) *Return per trade distribution*



(b) *Monthly return distribution*

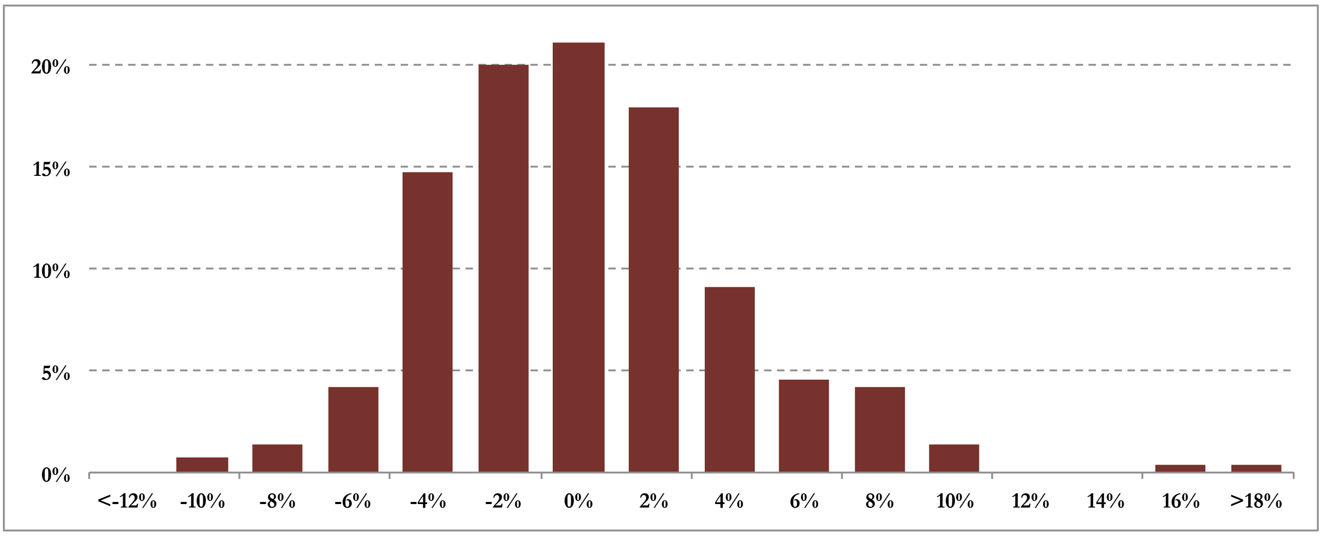


Figure 2a (2b) displays the return distribution for the trend following strategy per trade (month). The strategy results in a high number of trades with small negative returns and a low number of trades with high positive return. This results in a non-symmetric, positively skewed return distribution, which is also shown in Table 1. Results are in accordance with Clenow (2013) and Greyserman and Kaminski (2014), who also find a positively skewed return per trade distribution. The monthly returns also display a non-symmetric distribution with a fatter tail on the right side, indicating a positive skew, which also is highlighted in Table 2.

6.2 Alpha and factor loadings

6.2.1 Exposure to theoretical risk factors

In order to explore the systematic risk exposure of the trend following strategy, the monthly excess return of the strategy is regressed on six standard theoretical risk factors. Factors include the risk premia attributable to market, size, value (Fama and French 1993), cross-sectional momentum (Carhart 1997), short-term reversals (Jegadeesh 1990) and long-term reversals (De Bondt and Thaler 1985). The independent variable are as follow: *MKT-Rf*, *SMB*, *HML*, *UMD*, *STR* and *LTR*.

Table 3
Exposure to Fama French long-short risk factors

The dependent variable is the trend following strategy's monthly return above the risk free rate. The investment universe consists of 76 global futures contracts and the trading rules applied correspond to the break-out strategy. Return is based on total portfolio value and is net of trading costs. Independent variables are the risk premia attributable to market (MKT-Rf), size (SMB), value, (HML), cross-sectional momentum (UMD), short-term reversals (STR) and long-term reversals (LTR). Autocorrelation and heteroskedasticity consistent Newey-West HAC t-statistics are reported in parentheses. Adjusted R-square, F-statistics and number of observations (N) are reported. The sample period runs from January 1990 to September 2013 (285 observations).

	(1)	(2)	(3)	(4)	(5)	(6)
Intercept	0.010***	0.010***	0.010***	0.009***	0.009***	0.009***
	(4.53)	(4.56)	(4.49)	(4.05)	(4.16)	(4.23)
MKT-Rf	-0.088	-0.077	-0.083	-0.047	0.002	-0.001
	(-0.92)	(-0.78)	(-0.82)	(-0.47)	(0.02)	(-0.01)
SMB		-0.055	-0.068	-0.078	-0.067	-0.090
		(-0.63)	(-0.77)	(-0.95)	(-0.92)	(-1.00)
HML			-0.047	-0.016	-0.007	-0.031
			(-0.65)	(-0.24)	(-0.11)	(-0.33)
UMD				0.101*	0.076*	0.072
				(1.94)	(1.67)	(1.49)
STR					-0.215***	-0.215***
					(-2.84)	(-2.84)
LTR						0.056
						(-0.44)
Adj R-square	0.009	0.011	0.012	0.026	0.060	0.061
F-statistics	2.625	1.586	1.166	1.890	3.556	2.994
N	285	285	285	285	285	285

*p<=0.10, **p<=0.05, ***p<=0.01

Table 3 documents the risk exposure of the trend following strategy using six different factor model specifications for the sample period January 1990 to September 2013. Results indicate that the excess return of the strategy cannot be fully explained by exposure to the systematic risk factors. The estimated intercept is positive and statistically significant at a confidence level above 99% across the different model specifications, ranging from 1.0% when only including the market factor as an explanatory variable to 0.9% when evaluating the complete six-factor model. This finding is in line with Moskowitz, Ooi and Pedersen (2012), who find that time series momentum earns a premia above the Fama French four factor model.

Exposure toward the market factor is negative but not statistically significant at a reasonable confidence level. This finding is in line with Hurst, Ooi and Pedersen (2012), that document a negative correlation between their trend following strategy and the S&P 500 Index. Moskowitz, Ooi and Pedersen (2012) find that time series momentum carries a positive, but insignificant exposure to the market factor. The exposures to the size- and value factor are negative but not significant, which is line with

Moskowitz, Ooi and Pedersen (2012). Exposure toward the cross-sectional momentum factor is positive and significant at a confidence level above 90% in model specification four and five. However, in the final model specification, the confidence level drops and the null hypothesis that the true coefficient is zero cannot be rejected. Moskowitz, Ooi and Pedersen (2012) find that the time series momentum factor experiences a positive and significant exposure toward the cross-sectional momentum factor. Thus, the trend following strategy carries a lower exposure to the cross-sectional momentum factor than the time series momentum factor. The loading on short-term reversals is negative and significant. This finding is intuitive, as the evaluation period and average holding period employed in the trend following strategy is similar to the short-term reversal factor, but with the opposite positions being executed. Exposure toward the long-term reversal factor is positive but not significant.

Adjusted R-square of the model is below 0.07 for all model specifications, indicating a low explanatory power of the chosen factors. This is accordance with Moskowitz, Ooi and Pedersen (2012), who find a low explanatory power of the Fama French four factor model on the time series momentum factor. Arguably, the low explanatory power is driven by the constructing of the factors. The factors are based on equity returns whereas the trend following strategy is invested in a number of asset classes besides equities. These findings indicate that the standard risk factors are not able to explain the return of the trend following strategy and hence, further common sources of return need to be examined.

Recent presented risk factors in the momentum literature are value everywhere (Asnesss, Moskowitz and Pedersen 2013), momentum everywhere and time series momentum (Moskowitz, Ooi and Pedersen 2012). In Table 4, excess return of the strategy is regressed on these factors. The excess return of the market is included as a control variable. The independent variables thus include: *MKT-Rf*, *MOM EV*, *VAL EV* and *TS MOM*.

Table 4
Exposure to Pedersen long-short risk factors

The dependent variable is the trend following strategy monthly return above the risk free rate. The investment universe consists of 76 global futures contracts and the trading rules applied correspond to the break-out strategy. Return is based on total portfolio value and is net of trading costs. Independent variables are risk the premia attributable to market (MKT-Rf), value everywhere (VAL EV), momentum everywhere (MOM EV) and time series momentum (TS MOM). Autocorrelation and heteroskedasticity consistent Newey-West HAC t-statistics are reported in parentheses. Adjusted R-square, F-statistics and number of observations (N) are reported. The sample period runs from January 1990 to December 2012 (276 observations).

	(1)	(2)	(3)	(4)
Intercept	0.009***	0.008***	0.008***	0.004**
	(4.58)	(3.99)	(3.72)	(2.10)
MKT-Rf	-0.074	-0.042	-0.042	-0.055
	(-0.73)	(-0.40)	(-0.41)	(-0.63)
MOM EV		0.373***	0.373***	-0.34*
		(3.56)	(2.63)	(-1.95)
VAL EV			0.000	-0.265
			(0.00)	(-1.59)
TS MOM				0.622***
				(6.88)
Adj R-square	0.007	0.048	0.048	0.222
F-statistics	1.873	6.838	4.542	19.353
N	276	276	276	276

*p<=0.10, **p<=0.05, ***p<=0.01

Table 4 presents the exposure of the trend following strategy using four different factor model specifications for the sample period running from January 1990 to December 2012.[5] The estimated intercept is positive, ranging from 0.9% to 0.4%, and statistically significant at a confidence level above 99% in the first three model specifications. When the time series momentum factor is included, in the final model specification, the confidence level drops to 95% and the magnitude of the intercept drops to 0.4%.

The trend following strategy's exposure to the momentum everywhere factor is positive and statistically significant at a confidence level above 99% in model specification two and three. When the time series momentum factor is included, the estimated coefficient turns negative and the significance level drops. This result indicates a strong positive correlation between the momentum everywhere factor and the time series momentum factor, which is in line with Asness, Moskowitz and Pedersen (2013). Thus, there is an omitted variable bias present in model specification two and three and the estimated coefficient for the exposure toward the momentum everywhere factor is overestimated (Wooldridge 2008). Hence, the trend following strategy is associated with a negative and marginally significant exposure toward the momentum everywhere factor. This finding is somewhat puzzling but likely driven by the shorter evalua-

[5]The *VAL EV* and *MOM EV* factors are only available to December 2012.

tion period employed in the trend following strategy (50 days compared to an 11 months evaluation period for the momentum everywhere factor). Exposure to the value everywhere factor is marginally negative but not significant at a reasonable confidence level. This is somewhat contradictory to Moskowitz, Ooi and Pedersen (2012), establishing a positive and significant exposure of the time series momentum factor to the value everywhere factor. This discrepancy is again likely driven by the shorter evaluation period employed in the trend following strategy, whereas the value everywhere and time series momentum factor are defined over the same evaluation period. The trend following strategy's loading on the time series momentum factor is positive and significant. The estimated coefficient equals 0.62, indicating a high economic significance.

When including the time series momentum factor, the explanatory power of the independent variables increase from 0.05 to 0.22. Hence, a considerable part of the excess return stemming from a trend following strategy can be explained by the time series momentum factor.

6.2.2 Exposure to major asset classes

In order to assess the trend following strategy's exposure to major asset classes, the monthly excess return of the strategy is regressed on the excess return of three major asset classes: equities, commodities and bonds. Indices used as proxy variables for the major asset classes are the Morgan Stanley Capital World Index, Goldman Sachs Commodity Index and Barclay Capital Bond Index. The explanatory variables thus include: *MSCI-Rf*, *GSCI-Rf*, *BCBI-Rf* and $MSCI^2$*-Rf* (capturing extreme movements in the stock market).

Table 5
Exposure to major asset classes

The dependent variable is the trend following strategy monthly return above the risk free rate. The investment universe consists of 76 global futures contracts and the trading rules applied correspond to the break-out strategy. Return is based on total portfolio value and is net of trading costs. Independent variables constitute the excess return of three indices, used as proxies for major asset classes: MSCI-Rf, GSCI-Rf, BCBI-Rf, and $MSCI^2$-Rf. Autocorrelation and heteroskedasticity consistent Newey-West HAC t-statistics are reported in parentheses. Adjusted R-square, F-statistics and number of observations (N) are reported. The sample period runs from January 1990 to September 2013 (285 observations).

	(1)	**(2)**	**(3)**	**(4)**
Intercept	0.009***	0.009***	0.010***	0.003
	(4.58)	(4.39)	(5.02)	(0.97)
MSCI-Rf	-0.073	-0.094	-0.101	-0.029
	(-0.73)	(-1.01)	(-1.11)	(-0.41)
GSGI-Rf		0.064	0.066	0.090*
		(0.95)	(0.97)	(1.74)
BCBI-Rf			0.222	0.272
			(0.84)	(1.31)
$MSCI^2$-Rf				3.351
				(1.31)
Adj R-square	0.007	0.016	0.019	0.093
F-statistics	1.87	2.22	1.81	7.17
N	285	285	285	285

*p<=0.10, **p<=0.05, ***p<=0.01

Table 5 presents the exposure of the trend following strategy using four different factor model specifications for the sample period running from January 1990 to September 2013. The estimated intercept is positive and statistically significant at a confidence level above 99% in the first three model specifications, ranging from 0.9% to 1.0%. In the final model specification, when the equity index squared is included as an explanatory variable, the intercept decreases in magnitude and the null hypothesis that the true intercept is zero cannot be rejected.

Exposure toward the equity index is negative and statistically insignificant, in agreement with Table 3 and Table 4, showing negative but insignificant exposure to the Fama French market factor. Exposure toward the commodity index is positive but not significant at a reasonable confidence level in model specification two and three. T-statistic for the final model specification is 1.74 and hence, the exposure is significant at a 90% confidence level. It is expected that the excess return from the strategy loads positively on the commodity index, since the long leg of the agricultural sector is one of the main profit driver components of the strategy. Nevertheless, the estimated coefficient in the final model specification equals 0.09, indicating a low economic significance. Exposure toward the bond index is positive but not significant. When including the equity index squared as an explanatory variable, the exposure is observed to be positive but not significant. This result indicates that the trend following strategy benefits from extreme events in the stock market. This finding is in line with Hurst, Ooi and Pedersen (2012) who find that time series momentum is associated with positive returns in nine out of the ten worst economic drawdowns in the last 110 years. Also, Moskowitz, Ooi and Pedersen (2012) find that the time series momentum factor carries positive and significant exposure to the equity index squared, on a quarterly basis.

The adjusted R-square is found in the range between 0.01 and 0.09, increasing considerably when including the equity index squared as an explanatory variable.

6.3 Evaluation of the trend following strategy in relation to industry benchmark

Figure 3
Cumulative return indices for the trend following strategy and industry benchmark

The figure plots cumulative return indices based on the trend following strategy's monthly return. The y-axis shows the cumulative index with a base of 100, where the scale is logarithmic. The investment universe consists of 76 global futures contracts and the trading rules applied correspond to the break-out strategy. Return is based on total portfolio value. Gross return is net of transaction costs and gross of fees. Net return is net of transaction costs and net of fees. Fees are assumed to constitute a 2% management fee per year and a 20% performance fee including a high water mark, disbursed on a monthly basis. The graph also includes a cumulative return index based on the monthly return of the managed futures benchmark CS Man Fut. The benchmark measures the aggregated performance of managed futures funds, net of fees. The sample period is January 1994 to September 2013 (237 observations).

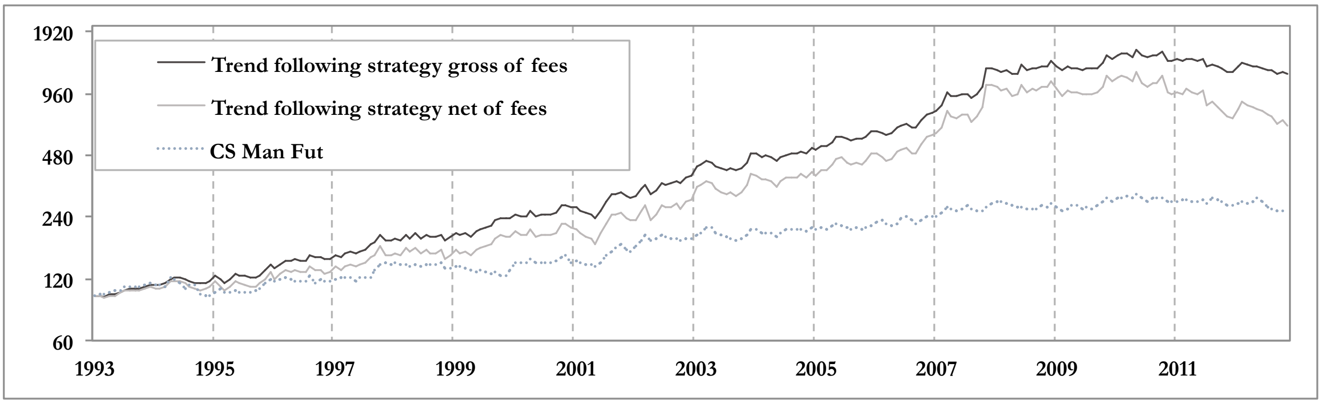


Figure 3 displays the cumulative return index for the trend following strategy and the Credit Suisse Managed Futures Index (*CS Man Fut*), employed as a benchmark to evaluate the trend following strategy. The net return of the strategy is based on an assumption of a 2% management fee per year and a 20% performance fee, including a high water mark, following the standards in the hedge fund industry (Fung and Hsieh 2011). A high water mark means that performance fee is not paid unless the profit received makes the fund reach a new water mark. Fees are assumed to be disbursed on a monthly basis. This is conservative compared to industry standards but enables the creation of a, net of fees, monthly return vector that can be compared to the benchmark. Noticeable is that the index shows lower returns, compared to the strategy, in 2007 and 2008, but higher returns in 2011, 2012 and 2013. Readers are referred to Table 11 in Appendix for information of yearly net returns of the benchmark and the strategy.

In order to assess the trend following strategy's performance in relation to the benchmark, the monthly net return of the strategy above the risk free rate is regressed on the benchmark.

Table 6
Exposure to managed futures benchmark

The dependent variable is the trend following strategy monthly return above the risk free rate, net of fees. The investment universe consists of 76 global futures contracts and the trading rules applied correspond to the break-out strategy. Return is based on total portfolio value and is net of transaction costs. Fees are assumed to comprise annual management fee equal to 2% and performance fee equal to 20% including a high water mark, disbursed on a monthly basis. The independent variable is the net return above the risk free rate of the managed futures benchmark CS Man Fut. The benchmark measures the aggregated performance of managed futures funds. Autocorrelation and heteroskedasticity consistent Newey-West HAC t-statistics are reported in parentheses. Adjusted R-square, F-statistics and number of observations (N) are reported. The sample period runs from January 1994 to September 2013 (237 observations).

	(1)
Intercept	0.005**
	(2.10)
CS Man Fut	1.111***
	(10.00)
Adj R-square	0.422
F-statistics	174.960
N	237

*p<=0.10, **p<=0.05, ***p<=0.01

Table 6 presents the exposure of the trend following strategy toward the benchmark for the sample period running from January 1994 to September 2013.[6] The intercept is positive and statistically significant at a confidence level above 95%. The magnitude of the intercept equals 0.5% per month and hence, the economic significance is high. The strategy's exposure to the benchmark is positive and statistically significant at a confidence level above 99%. The coefficient is estimated to 1.1, indicating a high economic significance. The adjusted R-square amounts to 0.42, implying a high explanatory power of the benchmark.

[6] The Credit Suisse Managed Futures Index is only available from January 1994.

6.4 Diversification benefits

Table 7

Monthly return characteristics for the trend following strategy and benchmarks

Monthly return characteristics for the equity index MSCI, the bond index BCBI and the trend following strategy, TF. The combination 60/40 refers to a portfolio that is 60% invested in MSCI and 40% invested in BCBI. The TF-portfolio refers to a portfolio that is 75% invested in the 60/40 portfolio and 25% invested in the trend following strategy. For the trend following strategy, the investment universe consists of 76 global futures contracts and the trading rules applied correspond to the break-out strategy. Return is based on total portfolio value and is net of trading costs. Volatility refers to standard deviation and absolute kurtosis is reported. MDD represents maximum drawdownand $Mean\ ret_{t:t+18}|ret_{t-6:t} < 0$ *measures the mean return for the coming 18 month, conditional on the return being negative in the preceding 6 months. Sharpe ratio measures excess return, above the risk free rate, divided by volatility. Sortino ratio measures excess return divided by downside volatility. Alpha above MSCI is the intercept of a regression, where excess return of MSCI is the only independent variable. Beta to MSCI is the estimated coefficient for exposure toward the MSCI, obtained from the same regression. The sample period runs from January 1990 to September 2013 (285 observations).*

				Combinations	
	MSCI	**BCBI**	**TF**	**60/40**	**TF-portfolio**
Summary statistics					
Mean	0.45%	0.02%	1.18%	0.28%	0.50%
Volatility	4.45%	1.07%	4.06%	2.75%	2.23%
Negative Volatility	3.33%	0.71%	1.85%	2.05%	1.22%
Minimum	-19.05%	-3.13%	-9.62%	-12.48%	-4.99%
Maximum	10.91%	3.66%	22.94%	7.09%	6.66%
Skewness	-0.646	-0.213	0.899	-0.678	-0.016
Kurtosis	4.244	3.449	5.966	4.450	2.802
Left-tail risk					
Maximum Drawdown	55.37%	12.07%	23.79%	37.90%	20.55%
95% Value at Risk	6.87%	1.75%	5.50%	4.24%	3.17%
Expected Shortfall	10.13%	2.31%	7.20%	6.16%	4.07%
$Mean\ ret_{t:t+18}\|ret_{t-6:t} < 0$	7.47%	0.51%	18.28%	4.52%	7.77%
Reward to risk					
Sharpe ratio	0.042	-0.232	0.226	0.005	0.107
Sortino ratio	0.056	-0.350	0.495	0.006	0.195
Portfolio perspective					
Alpha to MSCI		-0.003	0.009	-0.001	0.002
Beta to MSCI		0.026	-0.074	0.610	0.439
Return during MSCI Max DD		-0.97%	63.76%	-37.90%	-19.29%

Table 7 presents the return characteristics of the equity index *MSCI*, the bond index *BCBI* and the trend following strategy for the time period January 1990 to September 2013. It also presents the return characteristics of a classical 60/40 portfolio and a more dynamic, extended 60/40 portfolio, that is 75% invested in the 60/40 portfolio and 25% invested in the trend following strategy. The latter portfolio is henceforth referred to as the TF-portfolio.

Assessing the summary statistics for the evaluated time period, the trend following strategy (bond index) is associated with the highest monthly average return, amounting to 1.18% (0.02%). The equity index and the trend following strategy display the highest standard deviation (4.45% versus 4.06%) while the bond index is associated with the lowest standard deviation (1.07%). When considering downside volatility, the equity index and the 60/40 portfolio show the highest volatility, while the bond index and the TF-portfolio are associated with the lowest volatility. The equity index (trend following strategy) is associated with the most extreme minimum (maximum) return. Skew as well as kurtosis is high for the trend following strategy (0.90 and 5.97). The equity index is associated with negative skewness and excess kurtosis, which is not reduced when constructing a 60/40 portfolio. The characteristics of the equity index and the 60/40 portfolio are more in line with a convergent strategy, as outlined in Rzepczynski (1999). However, when including a trend following component to the 60/40 portfolio, the negative skew is reduced significantly and the kurtosis is considerably lower.

Evaluating the left-tail risk measures: maximum drawdown, value at risk and expected shortfall, all three measures are highest (lowest) for the equity index (bond index). All three measures are enhanced when including a trend following component to a standard 60/40 portfolio. $Ret_{t:t+18}|Ret_{t-6:t} < 0$ measures the expected return in the coming 18 month, conditional on the return being negative in the preceding 6 months, measuring the rate of recovery following a drawdown. The conditional expected return is highest (lowest) for the trend following strategy (bond index). This finding is in line with Greyserman and Kaminski (2014), describing a high recovery ability of a trend following strategy. The inclusion of a trend following component to a 60/40 portfolio results in a considerable increase of the conditional expected return.

The trend following strategy is associated with the highest return to risk (measured by Sharpe and Sortino ratio) while the bond index is associated with negative reward to risk. When adding a trend following component to a 60/40 portfolio, the return to risk increases considerably. The Sortino ratio shows the largest increase, indicating that downside volatility is reduced. This is in line with previous research and arguable the strongest argument to include a convergent component (Tomeo, Rosenberg and Chung 2004).

Finally, the excess return of the bond index, the 60/40 portfolio and the TF-portfolio is regressed upon the excess return of the equity index. For the bond index and the 60/40 portfolio, a negative alpha is documented. The trend following strategy and the TF-portfolio on the other hand, yield a positive alpha. Moreover, the 25% allocation to the trend following strategy reduces the exposure to the market, compared to the standard 60/40 portfolio. Measuring the return during the equity index maximum drawdown, the trend following strategy displays a return of 63.76% while the 60/40 portfolio displays a return of negative 37.90%. Hence, when migrating to a more dynamic portfolio that includes a quarter of the trend following strategy, the negative return during the equity drawdown is less extreme.

7 Tail Events and Implementability

In 2008 the world equity market, proxied by the Morgan Stanley Capital World Index, dropped by 42%. During the same time period, the Credit Suisse Managed Futures Index rose 18.3%. Gross of fees and net of trading costs the trend following strategy increased by 58.3% (see Table 10 in Appendix for yearly performance of the strategy). Net of trading costs and fees, the return realised to investors would have been 44.7% (see Table 11 in Appendix for yearly net return of the strategy and the benchmark). Such outsized returns are in line with Clenow (2013) and could also be observed among CTA funds. E.g. Lynx Hedge observed a net return equal to 42% (Lynx 2014) and the corresponding number for ISAM equals 78% (ISAM 2014).

Table 8
Trend following strategy tail events

Return for the trend following strategy in February and October 2008, representing the most extreme months for the strategy. The investment universe consists of 76 global futures contracts and the trading rules applied correspond to the break-out strategy. Return is based on total portfolio value and is net of trading costs. Long (short) leg represents long (short) positions in the futures contracts and sector represents sector of the underlying assets. The sample period runs from January 1990 to September 2013 (285 observations).

	Complete Strategy	Long Leg	Short Leg
February 2008	16.838%	17.153%	-0.572%
October 2008	22.937%	-0.672%	23.206%

	Agricultural	Currency	Equity	Non-agricultural	Rate
February 2008	9.374%	2.268%	0.152%	4.345%	0.443%
October 2008	7.110%	5.288%	4.380%	3.805%	1.952%

Table 8 presents return per leg and sector, for the most extreme months of the trend following strategy; February and October 2008. For monthly performance of the strategy, readers are referred to Table 12 in Appendix. In February, the long leg of the strategy is driving the return, whereas it is the short leg that is driving the return in October. As markets were characterised by fear and greed at this time, volatility and trendiness of the market were extreme (CBOE 2014). In February, the Wheat (Soybeans) futures contract had soared by 120% (80%) in the midst of what, post 2008, is referred to as the commodity rally (Dorch 2009). In October the same year, the financial crisis struck, Lehman Brothers had gone bankrupt, the TED-spread reached previously unprecedented levels and consumer spending fell sharply (Altman 2008). The majority of the returns of the strategy stemmed from trades within the agricultural sector, but positive returns where realised in all of the sectors in both of the extreme months. This suggests that the strategy did not only benefit from a single trade, but rather from several trades within different sectors.

The extreme returns observed in 2008 raise the question of potential implementability issues of the trend following strategy during the sample period. As the strategy assumes entering and exiting of positions at the closing price of the day following the trading signal, the strategy is already conservative. However, the assumptions regarding margin requirements should be highlighted. A reasonable concern would be that initial margin requirements during the financial crisis might have risen to levels where the strategy wouldn't have been feasible due to practical constraints. If initial margin requirements across contracts would simultaneously rise considerably and aggregated margin requirements would exceed total portfolio value, the trend following strategy would have had to scale down its positions.

Table 13 (see Appendix) presents actual initial margin requirements for four representative futures contracts in different sectors (one per sector).[7] During most of 2008, requirements are well within the bound of the assumptions outlined in Section 5. In October to November of 2008, initial margin requirements increases (as expected, given the turbulent time). Figure 6 (see Appendix) displays the margin to equity in 2008, assuming that initial margin requirements correspond to the highest level observed in each sector in 2008. The figure shows that the increase in initial margin requirements would not have posed any issues with respect to the implementation of the strategy. The margin to equity ratio is still on a reasonable level. Due to the positing sizing formula (recall equation 13 in the Methodology section) a high volatility in the underlying markets will result in smaller positions and in the extension, lower exposure. Thus, when volatility is high the strategy automatically scales down the position. In conclusion, the returns achieved in 2008 are reasonable with respect to implementation. This finding is also supported by the aforementioned anecdotal evidence of outsized CTA funds returns in 2008.

[7] Historical margins for the fifth sector (non-agricultural) are not available. CME group does not has data on historical margins for the non-agricultural sector prior to 2009 when they acquired NYMEX.

8 Parameter Stability

Results are only as good as the inputs and therefore it is necessary to discuss the robustness of the results, by varying the input parameters of the trend following strategy. Optimisation of the input parameters is avoided and sensitivity intervals are arbitrary chosen, but centered around the initial inputs of the strategy. Table 14 (see Appendix) presents the results of iterations of five key parameters. The parameters are: 1) theoretical risk level per contract denominated in basis point ($risk$), 2) number of days used in calculation of exit and entry triggers (break-out window), 3) number of days used in moving average computation with respect to trend filter calculation, 4) stop/loss trigger and 5) average trading range (ATR), used as input in the position sizing formula and stop/loss mechanism.

The risk interval subject to the sensitivity analysis is 7.5 +/- 1.0 basis points per contract. The mean return, maximum drawdown, standard deviation and the level of intercepts in the regressions increase with the level of risk applied. Results indicate that the intercept above the Pedersen long-short risk factors (value everywhere, momentum everywhere and time series momentum) and the managed futures benchmark (The Credit Suisse Managed Futures Index) is positive and statistically significant on a confidence level above 95%, independent of the risk levels assessed.

The break-out window presents the trigger for the exit rule and the trigger for the entry rule. The window is robust as the return only shifts marginally when varying the window. The shorter window 15x30 leads to slightly higher mean return, but is on the other hand, associated with a larger maximum drawdown. Furthermore, the shorter window results in a higher number of trades. The longer window 50x100 is very similar to the base case.

With respect to the horizon of the moving average, the parameters are robust when assessing the 50x100 and 75x150 moving average windows. When employing the short-term trend filter of 25x50, results are deteriorating. The average return drops and the standard deviation increases. This is expected since a shorter trend filter 25x50 would not capture the mid-term trends desired. In fact, the longer trend filter 75x150 results in better results than the original 50x100 window with regards to lower standard deviation and less extreme maximum drawdown.

When the stop/loss execution is set at 2 ATR units away from the highest high or the lowest low, since initiation of the position, the average return decreases. When increasing the stop/loss to 4 ATR units the mean return increases but at the cost of a more extreme maximum drawdown as positions are exited at a later stage. Alphas and t-stats are again statistically significant at a confidence level above 95%, independent of the exact stop/loss level chosen.

Finally, the basis for calculation of the ATR is varied. When relaxing the 100 day assumption to a

75 and 125 window, similar results as the 100 day base case are observed. Hence, the choice of exact ATR window is also of less importance for the success of the strategy. Overall, the results show robustness to the input parameters assessed.

9 Conclusion

The purpose of this study has been to examine whether past prices and volatility can provide useful information that can be traded upon in a profitable way. It has also been to put a trend following strategy, based on a rule-based trading algorithm, into an academic context, by examining the practical implementability, sources of return and portfolio diversification potential. This has been enabled through the use of proprietary back adjusted continuous price series for 76 futures contracts, received from ACIES Asset Management.

With high positive risk-adjusted returns for the period investigated, our results accentuate the upsides of the trend following strategy. The investigation indicates a robust strategy with high applicability in futures markets. We find that the strategy carries low and statistically insignificant exposure to standard risk factors such as the risk premia attributable to market, value, size, cross-sectional momentum and long-term reversals. These findings are in accordance with previous research, e.g. Moskowitz, Ooi and Pedersen (2012) and Hurst, Ooi and Pedersen (2012). Our results suggest a significant and negative exposure to the short-term reversal factor. The alpha above the standard theoretical risk factors equals 0.9% on a monthly basis. Thus, we find evidence supporting sub hypothesis 1 outlined in Section 3.

The trend following strategy is associated with low and statistically insignificant exposure to major asset classes such as equities, commodities and bonds. Exposure toward the commodity index is marginally significant, although with a low economic significance. Loading on the squared term of the world equity index (used as a proxy for extreme movements in the equity market) is positive but not significant. Nevertheless, the inclusion of the variable increases the explanatory power considerably. This finding is in line with previous research, suggesting a high performance of the strategy during volatile periods in the market (e.g. Koulajian and Czkwianianc 2013).

Excess return of the trend following strategy is also regressed on recently presented risk factors in the momentum literature: value everywhere, momentum everywhere (Asness, Moskowitz and Pedersen 2013) and time series momentum (Moskowitz, Ooi and Pedersen 2012). These risk factors are, unlike the Fama French factors, constructed by evaluating a number of different asset classes in addition to equities. Our results indicate a positive and statistically significant exposure toward the time series momentum factor. Interestingly, the strategy delivers a positive and significant alpha above the factors. This implies that alpha stemming from acting on past information of prices can be achieved in several ways, through different rules and portfolio sorting methodologies. It also suggests that intuitive trading rules, based on past price movements, are efficient tools that can be utilised to create alpha and that such rules can refine and add upon the time series momentum risk premia. Key differences between the trend following strategy and time series momentum are more sophisticated trading rules (e.g. stop/loss mechanism and position sizing) and a shorter evaluation period (50 days in comparison to 11 months). These differences give rise to a monthly alpha of 0.4%. By regressing the trend following strategy excess returns, net of fees and trading costs, on the employed industry benchmark, we find that the strategy loads heavily on its industry counterpart. The estimated coefficient equals 1.1 and is significant. Nevertheless, the strategy yields a positive and significant intercept, amounting to 0.5% on a monthly basis. As the overall risk level results in an average margin to equity ratio of 12%, in line with industry standards, we conclude that the alpha is reasonable with respect to magnitude and significance. This validates sub hypothesis 3. A plausible explanation for this alpha is the fact that it is mainly related to the financial crisis where several managed future managers, making up the constituents of the benchmark, decided to overrule their previously set algorithms. This behavior has also been present in recent years; managers have tilted their portfolios toward the equity markets as trend following performance has been somewhat poor. This emphasises the importance of staying true to the basic rules of trend following, as a diversion from the core principals might result in missing out on some of the large positive outliers associated with the strategy.

We find that the return profile of the trend following strategy is associated with a positive skew, which is in accordance with previous research (e.g Clenow 2013). The skew is mainly driven by the short leg of the strategy. The stop/loss mechanism, forcing a netting of a position in order to avoid big losses, is also contributing to the positive skew. When comparing a standard 60/40 portfolio to a more dynamic portfolio, consisting of a 75% investment in the 60/40 portfolio and a 25% allocation to the trend following strategy, the latter portfolio displays beneficial portfolio characteristics. The dynamic portfolio shows higher mean return, lower volatility as well as more favorable left-tail characteristics with a less dramatic drawdown and higher rate of recovery following such. Reward to risk measures are also increasing and the beta toward equity markets decreases. These attributes confirm the diversification benefits and tail protection associated with a 25% allocation to the trend following strategy and support sub hypothesis 2.

As has been accounted for in this thesis, the inputs in the trend following strategy solely rely on past information of futures contracts prices. The results presented above, in combination with the findings of Moskowitz, Ooi and Pedersen (2012), challenge the critics of technical analysis and past prices as a predictor for future price paths. It highlights the strategy's favorable divergent return characteristics and emphasises its diversification benefits. Perhaps the drunkard referred to in the beginning of this thesis is more sober than what previously has been suggested. We find evidence that he is sober enough for investors to profit by identifying trends in his movements.

9.1 Limitations and suggestion for further research

Our suggestions for further research consider three aspects, relating to the limitations of our analysis: finding further explanatory variables for the excess return of the trend following strategy, the poor performance of the strategy in the recent years and the exploration of how the strategy could be improved as a diversification tool.

Although our results highlight that cross-sectional and time series momentum are integral components of a trend following strategy, the relatively low explanatory power of 0.22 suggests that there is more to the trend following story. Existing theoretical risk factors fail to explain a trend following strategy. Research on this topic is fairly limited and worth delving into. This also relates to the qualitative explanation of why trends exist which is addressed by Moskowitz, Ooi and Pedersen (2012), relating to hedger and speculator demand asymmetries as well as behavioral explanations. One suggestion would be to construct a risk factor based upon hedging demand to investigate how much of trend following excess return can be explained by non profit maximising agents.

Our results, as well as many of the well-known CTA funds results, show that recent performance of trend following strategies have been poor. By focusing on the distributional characteristics of a trend following strategy in recent years, further research could shed light on why the return profile have changed, and whether this is a structural shift or a temporary state. Research on when a trend following strategy performs well has been accounted for (e.g. Clenow 2013), but the potential to predict when trend following is going to provide high returns and risk allocate a portfolio based on market conditions is still fairly unexplored in the literature.

Finally, trend following as a strategy has shown superior hedging benefit and has, for over hundred years, shown evidence of low correlation to equity markets, as highlighted by Hurst, Ooi and Pedersen (2012). An interesting idea for future research would be to investigate if an even more unmitigated and pure diversification tool could be created successfully by increasing the level of sophistication in the trend following strategy. If so, it would certainly be of interest to investors seeking protection from an erosion of their capital base in times when markets turn south.

10 References

10.1 Periodicals

Asness, Clifford S, Moskowitz, Tobias J., Pedersen, Lasse H., 2013, Value and Momentum Everywhere, The Journal of Finance, Vol LXVIII.

Arrow, Kenneth. J., The Role of Securities in the Optimal Allocation of Risk-bearing, The Review of Economic Studies, Vol. 31, No. 2.

Bhojraj, Sanjeev, Swanibathan, Bhaskaran, 2006, Momentum: Returns Predictibility in International equity-indices, The Journal of Business, Vol 79, No 1.

Barberis, Nicholas, Huang, Ming, 2008, Stocks as Lotteries: The Implications of Probability Weighting for Security Prices, American Economic Review, Vol. 98, No.5.

Barberis, Nicholas, Thaler, Richard, 2003, A Survey of Behavioral Finance, Handbook of the Economics of Finance.

Chung, Sam, Rosenberg, Mark, Tomeo, James F, 2004, Hedge Fund of Fund Allocations Using a Convergent and Divergent Strategy Approach, The Journal of Alternative Investments.

Carhart, Mark M., 1997, On Persistence in Mutual Fund Performance, The Journal of Finance, Vol. 52, No. 1.

Cootner, Paul H., 1964, The Random Character of Stock Market Prices, Cambridge, Mass. MIT Press.

DeBondt, Werne F.M., Thaler, Richard H., 1985, Does the Stock Market Overreact?, The Journal of Finance 40, pp 793-805.

Edwards, William D., 1968, Conservatism in human information processing. Formal Representation of Human Judgment (Wiley, New York).

Erb, Claude, Campbell Harvey, 2006, The Strategic and Tactical Value of Commodity Futures". Financial Analysts Journal Vol 62, No 2.

Fama, Eugene E., 1965, The Behavior of Stock-Market Prices, Journal of Business, Vol 30, No 1.

Fama, Eugene E., 1970, Efficient capital markets: A Review of Theory and Empirical Work, Journal of Finance 25, pp 383-417.

Fama, Eugene E., French, Kenneth R, 1993, Common Risk Factors in the Returns on Stocks and Bonds, The Journal of Financial Economics 33, pp 3-56.

Fung, William, Hshiehb, David A., 2011, The Risk in Hedge Fund Strategies: Theory and evidence from long/short equity hedge funds. Journal of Empirical Finance, Vol 18, Issue 4

Frazzini, Andrea, 2006, The Disposition Effect and Underreaction to News, Vol 61, Issue 4, pp 2017?2046.

Grinblatt, Mark, Titman, Sheridan, Russ, Wermers, 1995, Momentum Investment Strategies, Portfolio Performance, and Herdings: A Study of Mutual Fund Behavior, The American Economic Review, Vol 85, No 5.

Hurts, Brian, Ooi, Yao H., Pedersen, Lasse H., 2012, A Century of Evidence on Trend-Following Investing. AQR Capital Management.

Jegadeesh, Narasimhan, Titman, Sheridan, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency. The Journal of Finance, Vol. 48, No. 1.

Jegadeesh, Narasimhan, Titman, Sheridan, 1990, Evidence of Predictable Behavior of Security Returns. Journal of Finance, Vol 45.

Jegadeesh, Narasimhan, Titman, Sheridan, 2011, Momentum, The Annual Review of Financial Economics, Vol. 3, pp 493-509.

James, Jessica, Colchester, Hetty, 2004, Enhancing Trend-Following Strategies with Option Selling, Quantiative Finance, Vol. 4, Issue 1.

Kahneman, Slovic, Paul, Daniel, Tversky, Amos, 1974, Judgment under Uncertainty: Heuristics and Biases, Cambridge University Press

Kahneman, Slovic, Paul, Daniel, Tversky, Amos, 1979, Prospect Theory: An Analysis of Decision under Risk, Econometrica, Vol. 47, No. 2.

Lo, Andrew, 2004, The Adaptive Market Hypothesis: Market Efficiency from an Evolutionary Perspective, The Journal of Portfolio Management, Vol. 30, No. 5.

Lo, Andrew, 2005, Reconciling Efficient Markets with Behavioral Finance: The Adaptive Markets Hypothesis, The Journal of Investment Consulting, Vol. 7, No. 2.

Lo, Andrew, Mamaysky Harry, Wang, Jiang, 2000, Foundation of Technical Analysis: Computations Algorithms, Statistical Inference and Empirical Implementation, The Journal of Finance, Vol LV, No 4.

Leland, Hayne E., 1999, Beyond Mean-Variance: Performance Measurement in a Nonsymmetrical World, Financial Analysts Journal, January/February 1999.

Moskowitz, Tobias J., Ooi, Yao H., Pedersen, Lasse H. 2012, Time Series Momentum, Journal of Financial Economics, 104.

Pratt, John, W., 1964, Risk Aversion in the Small and in the Large, Econometrica, Vol. 32, No. 1/2.

Rzepczynski, Mark S., 1999, Market Vision and Investment Styles: Convergent versus Divergent Trading, Practitioners Corner, Winter 1999.

Shleifer, Andrei, Summers, Lawrence H., 1990, The Noise Trader Approach to Finance. Journal of Economic Perspectives Vol 4, No 2.

10.2 Working papers

Daniel, Kent and Moskowitz, Tobias J., 2011, Momentum Crashes, Working paper (Columbia Business School).

Grinblatt, Mark, Han, Bing, 2001, The Disposition Effect and Momentum, Working Paper (University of California, Los Angeles, CA).

Mullainathan, Sendhil, 2001, Thinking Through Categories, Working Paper (MIT, Cambridge).

10.3 Books

Clenow, Andreas F., 2013, Following the Trend, Wiley Trading.

Malkier, Burton, 1973, A Random Walk Down Wall Street. W.W. Norton & Company.

Veronesi, Pietro, 2010, Fixed Income Securities: Valuation, Risk, and Risk Management. Wiley Investment Management.

Wooldridge, Jeffrey M., Introductory Econometrics, A Modern Approach, South Western Cengage Learning, Fourth Edition.

Greyserman, Alex and Kaminski, Kathryn M., 2014, Trend Following with Managed Futures, The Search For Crisis Alpha, Wiley.

Ilmanen, Antti, 2011, Expected Returns: An Investor's Guide to Harvesting Market Rewards, Wiley Finance.

10.4 Data sources

CME Group, Chicago Mercentile Exchange, Initial margin requirements in 2008. Accessed: May 2014.

Datastream, Thomson Reuters Datastream, Subscription service. Accessed: March, 2014.

Bloomberg, Bloomberg LP, Subscription service. Accessed: February, 2014.

French, Kenneth R. "Kenneth French data library: Developed Market Factors and Returns", Accessed online: [*mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html*] (February 2014)

Pedersen, Lasse H. "Lasse H Pedersen research data", Accessed online: [*www.lhpedersen.com/data*] (April 2014)

10.5 Other sources

Altman, Roger, 2009, The Great Crash 2008, Foreign Affairs, January/February issue, Accessed online: [www.foreignaffairs.com/articles/63714/roger-c-altman/the-great-crash-2008/] (May 2014)

Authers, John, 2014, Nobel contradiction: Fama v Schiller, FT Long Short, Financial Times, October 14, Accessed online:

[blogs.ft.com/ft-long-short/2013/10/14/fama-shiller/] (May 2014)

CBOE, 2014, Chicago Board Option Exchange, Data of VIX on options and futures, Accessed online: [www.cboe.com/micro/vix/historical.aspx/] (May 2014)

Dorch, Gary, 2008, Central Bankers Fueling Global Commodity Inflation, Safe Heaven, Preservation of Capital, February 14, Accessed online: [www.safehaven.com/article/9471/central-bankers-fueling-global-commodity-inflation] (May 2014)

Iasg Group, Institutional Advisory Services Group, Data on margin to equity (self-reported numbers). Accessed online: [$http://www.iasg.com/managed-futures/performance$] (May 2014)

ISAM, International Standard Asset Management, Net return in 2008, Accessed online: [$www.managedfutures.com/program\_performance.aspx?fundtype = ev\&productid = 44500$] (May 2014)

Lynx, Lynx Hedge AB, Net return in 2008, Accessed online: [www.lynxhedge.se/avkastning–man] (May 2014)

11 Appendix

Table 9
Investment universe

Available futures contracts for the trend following strategy (76 contract), dichotomised into five sectors of the underlying assets: agricultural, currency, equity, non-agricultural and rate. The contracts are chosen based upon a high level of liquidity, received from Swiss based hedge fund ACIES Asset Management. Currency represents the currency that the contract is denoted in and point value is the size of the contract.

Aggricultural sector (23 contracts)

Contract	Currency	Point value
Wheat-Milling	EUR	50
Soybean Oil	USD	600
Corn	USD	50
Cocoa	USD	10
Cotton	USD	500
Cattle-Feeder	USD	500
Rubber	JPY	5000
Coffee	USD	375
Lumber	USD	110
Live Cattle	USD	400
Lean Hogs	USD	400
Robusta Coffee	USD	10
Sugar (White)	USD	50
Maize-White	ZAR	100
Wheat-Spring	USD	50
Oats	USD	50
Orange Juice	USD	150
Rice (Rough)	USD	2000
Rapeseed (Canola)	CAD	20
Soybean	USD	50
Sugar	USD	1200
Soybean Meal	USD	100
Wheat	USD	50

Currency sector (11 contracts)

Contract	Currency	Point value
AUD/USD	USD	100000
GBP/USD	USD	62500
CAD/USD	USD	100000
EUR/USD	USD	125000
USD Index	USD	1000
JPY/USD	USD	125000
NZD/USD	USD	100000
EUR/CHF	CHF	125000
EUR/GBP	GBP	125000
EUR/GBP	GBP	125000
EUR/JPY	JPY	125000
CHF/USD	USD	125000

Equity sector (16 contracts)		
Contract	**Currency**	**Point value**
S&P 500 (E-mini)	USD	50
CAC 40	EUR	10
DAX	EUR	25
FTSE 100	GBP	10
Hang Seng China Enterprises Index	HKD	50
Hang Seng	HKD	50
Nikkei 225	USD	5
Nasdaq (E-mini)	USD	20
OMXS30	SEK	100
MSCI Singapore Stock-SGX	SGD	200
MSCI Taiwan	USD	100
Euro Stoxx 50	EUR	10
S&P TSX 60	CAD	200
Russel 2000 (E-mini)	USD	100
SPI (Australia)	AUD	25
Non-agricultural sector (11 contracts)		
Contract	**Currency**	**Point value**
Crude Oil	USD	1000
Gold	USD	100
Copper	USD	250
Heating Oil	USD	42000
Brent Crude	USD	1000
Petroleum Gas Oil	USD	100
Natural Gas	USD	10000
Palladium-NYMEX	USD	100
Platinum	USD	50
Petroleum Gasoline Reformulated Blendstock	USD	42000
Silver	USD	5000
Rate sector (15 contracts)		
Contract	**Currency**	**Point value**
Bankers' Acceptance-Canadian 3Mth-ME (24 hr)	CAD	2500
CAD Treasury 10yr	CAD	1000
EUR Bund 10yr	EUR	1000
EUR Bobl 5yr	EUR	1000
EUR Schatz 2yr	EUR	1000
Eurodollar 3m	USD	2500
Euribor	EUR	2500
GBP Gilt 10yr	GBP	1000
Short Sterling	GBP	1250
US Treasury Note 5yr	USD	1000
Govt Bond-Japanese10Yr	JPY	1000000
US Treasury Note 2yr	USD	2000
US Treasury Note 10y	USD	1000
US Treasury Long Bond 30yr	USD	1000
Bank Bills-Australian (90 day)	AUD	2400

Figure 4
Back adjustment of price series

Back adjusted and unadjusted price series for the futures contract on AUD/USD (used as an example). Due to a limited life span of futures contracts, a number of different contracts must be linked together in order to construct a continuous time series of prices. For unadjusted price series, the prices are simply put after each other. The difference in prices will result in a negative or positive gap when you switch (roll over) between contracts with different maturities. Such artificial gaps need to be removed in order to receive a continuous time series that reflects the market behavior. The adjustment is performed by linking the contracts together so that the old contract's closing price match the new contract's closing price on the roll over date. This means that the time series back in time will shifted up or down (depending on the term structure) to match the new series. The last price of the time series will always be correct but previous adjusted prices will have a mismatch with the actual price at the time. Subfigure (a) shows the time period January 1st 1990 to November 13th 2013 (6209 observations). Subfigure (b) zooms in on a shorter time period, spanning from July 2nd 2013 to November 13th 2013 (96 observations).

(a) *January 1st 1990 to November 13th 2013*

(b) *July 2nd 2013 to November 13th 2013*

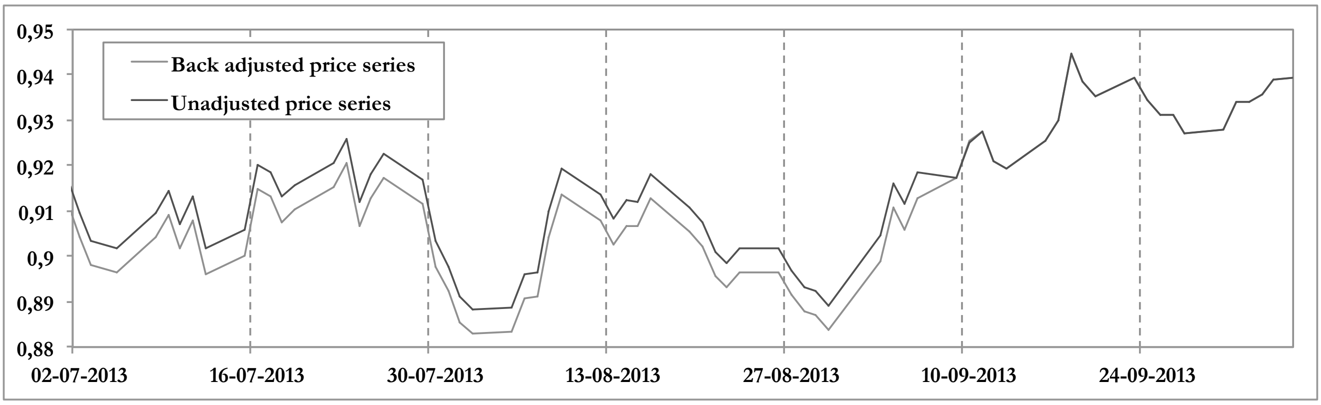


Figure 5
Trading strategy example

Open long trade period shaded in grey, closing price, highest close in the preceding 50 days, lowest closing price in the last 25 days and trend filter, for the futures contracts on cocoa. A long trade is initiated if today's closing price is equal to, or higher than, the highest closing price in the preceding 50 days and the trend filter points in the same direction as the trading signal. The trend filter allows for a long position if the 50 days moving average of the closing price is above the 100 day moving average. The trade is closed if the closing price is equal to, or lower than, the lowest closing price in the preceding 25 days or the stop/loss mechanism is executed. The y-axis presents the price of the futures contract, measured in USD per ton cacao. The sample period runs from October 31st 2007 to October 31st 2008 (262 observations).

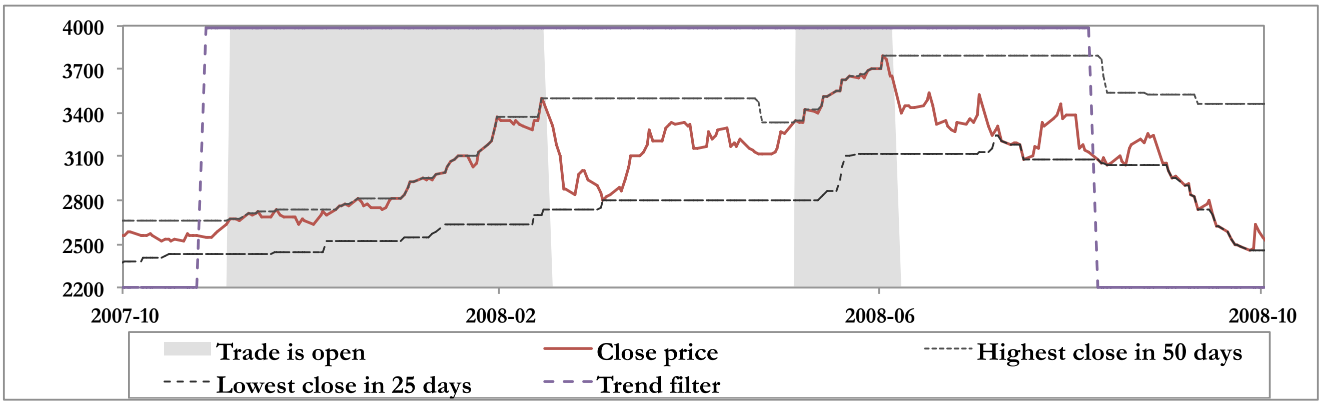


Table 10
Trend following strategy yearly performance

Yearly return for the trend following strategy. The investment universe consists of 76 global futures contracts and the trading rules applied correspond to the break-out strategy. Return is based on total portfolio value and is net of trading costs. Long (short) leg represents long (short) positions in the futures contracts and sector represents that of the underlying asset. The sample runs from 1990 to 2012 (23 observations).

				Sector				
Year	**Complete strategy**	**Long Leg**	**Short Leg**	**Agricultural**	**Currency**	**Equity**	**Non-agricultural**	**Rate**
1990	23.3%	3.3%	11.0%	8.2%	5.6%	0.0%	-2.3%	2.8%
1991	27.1%	22.6%	2.1%	6.2%	2.6%	-1.5%	-1.3%	18.5%
1992	11.3%	6.2%	3.3%	4.8%	-3.1%	3.8%	2.9%	2.5%
1993	6.6%	11.9%	-8.9%	3.1%	-2.8%	-0.7%	5.9%	-0.2%
1994	11.3%	11.9%	-6.4%	15.7%	-0.7%	-7.9%	-6.4%	5.6%
1995	11.8%	11.8%	-8.7%	2.5%	-8.3%	1.2%	4.6%	7.9%
1996	7.6%	5.1%	-5.5%	1.9%	-1.3%	2.7%	2.8%	-1.7%
1997	17.3%	3.8%	22.5%	6.5%	6.2%	4.9%	2.9%	2.6%
1998	19.5%	10.8%	16.3%	10.7%	-4.2%	2.1%	8.4%	10.6%
1999	6.6%	-5.2%	13.0%	6.1%	-7.1%	5.3%	0.2%	-3.7%
2000	23.8%	14.5%	22.5%	6.0%	20.5%	-19.7%	26.2%	15.7%
2001	7.3%	-7.7%	21.2%	5.2%	-11.7%	26.4%	1.9%	-4.1%
2002	13.7%	30.9%	-6.1%	5.1%	24.2%	-6.6%	-6.4%	24.9%
2003	40.1%	88.8%	-24.9%	11.9%	62.6%	33.0%	17.8%	28.2%
2004	15.5%	22.3%	-12.9%	10.7%	3.3%	6.2%	19.5%	12.4%
2005	3.4%	1.0%	-6.7%	9.7%	-4.6%	-12.0%	0.5%	-0.9%
2006	25.5%	19.0%	44.6%	4.4%	14.3%	96.0%	20.6%	-6.7%
2007	24.7%	28.5%	-5.3%	32.0%	23.6%	-20.1%	12.2%	35.4%
2008	58.3%	24.2%	336.3%	66.8%	50.7%	33.3%	78.9%	29.6%
2009	3.9%	14.2%	-17.3%	-7.9%	6.3%	33.6%	5.2%	-4.3%
2010	13.9%	25.5%	-10.5%	15.7%	27.6%	-2.6%	-10.5%	36.5%
2011	-5.6%	2.8%	-42.0%	-2.1%	-7.2%	-30.5%	-15.4%	10.0%
2012	-7.8%	-5.1%	-39.7%	-8.1%	-6.6%	-2.7%	-4.4%	-14.9%

Table 11
Performance of trend following strategy in comparison to managed futures benchmark

Starting net asset value (NAV), net return and ending NAV per year for the trend following strategy and the managed futures benchmark CS Man Fut. The benchmark measures the aggregated performance of managed futures funds. For the trend following strategy, the investment universe consists of 76 futures contract and trading rules applied correspond to the break-out strategy. Return is based on total portfolio value and is net of trading costs and fees. Fees are assumed to comprise annual management fee equal to 2% and performance fee equal to 20% including a high water mark, disbursed on a monthly basis. The time period runs from January 1994 to December 2012 (19 observations).

	Trend following strategy			CS Man Fut		
Year	**Start NAV**	**Net return**	**End NAV**	**Start NAV**	**Net return**	**End NAV**
1994	100.0	7.0%	107.0	100.0	11.9%	111.9
1995	107.0	7.5%	115.0	111.9	-7.1%	104.0
1996	115.0	4.1%	119.7	104.0	12.0%	116.5
1997	119.7	11.8%	133.9	116.5	3.1%	120.1
1998	133.9	13.6%	152.1	120.1	20.7%	144.9
1999	152.1	3.3%	157.1	144.9	-4.7%	138.1
2000	157.1	17.0%	183.8	138.1	4.3%	144.0
2001	183.8	3.9%	190.9	144.0	1.9%	146.7
2002	190.9	9.0%	208.0	146.7	18.3%	173.6
2003	208.0	30.1%	270.5	173.6	14.2%	198.2
2004	270.5	10.4%	298.5	198.2	6.0%	210.0
2005	298.5	0.7%	300.8	210.0	-0.1%	209.8
2006	300.8	18.4%	356.0	209.8	8.1%	226.7
2007	356.0	17.8%	419.3	226.7	6.0%	240.3
2008	419.3	44.7%	606.5	240.3	18.3%	284.3
2009	606.5	1.1%	613.4	284.3	-6.6%	265.6
2010	613.4	9.1%	669.4	265.6	12.2%	298.0
2011	669.4	-6.5%	626.2	298.0	-4.2%	285.6
2012	626.2	-8.2%	574.6	285.6	-2.9%	277.2
2013	574.6	-4.1%	551.0	277.2	-3.1%	268.7

Table 12
Trend following strategy monthly performance

Monthly return for the trend following strategy. The investment universe consists of 76 global futures contracts and the trading rules applied correspond to the break-out strategy. Return is based on total portfolio value and is net of trading costs. The trading period runs from January 1990 to September 2013 (285 observations). The two most extreme months, February and October 2008, are highlighted.

Year	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1990	2.6%	0.2%	2.5%	3.1%	-2.5%	3.8%	8.4%	-0.2%	3.2%	-1.4%	1.2%	0.7%
1991	-0.6%	0.3%	5.6%	-2.4%	0.9%	4.8%	-2.5%	-0.8%	4.8%	3.1%	0.5%	11.3%
1992	-3.6%	0.5%	-1.3%	-0.5%	1.1%	3.1%	4.6%	6.1%	-4.4%	3.1%	1.3%	1.3%
1993	-2.2%	4.3%	-1.3%	-1.1%	1.5%	0.1%	1.5%	-2.4%	-2.2%	0.6%	2.5%	5.4%
1994	-0.3%	-1.8%	2.9%	-0.1%	3.4%	2.3%	2.0%	-1.4%	1.1%	1.6%	2.3%	-1.1%
1995	0.0%	2.8%	5.2%	1.3%	-0.6%	-0.7%	-2.6%	-1.7%	-1.4%	0.9%	2.6%	5.7%
1996	-4.1%	-3.5%	4.4%	6.5%	-2.5%	-0.1%	-2.6%	1.2%	1.9%	5.4%	7.3%	-5.5%
1997	6.1%	3.9%	-0.2%	0.9%	-1.8%	1.5%	6.2%	-3.2%	-0.4%	-1.7%	1.5%	3.9%
1998	-2.4%	4.0%	2.8%	-2.2%	1.9%	1.2%	6.5%	3.4%	8.4%	-6.1%	0.2%	1.1%
1999	-1.6%	6.2%	-3.0%	4.9%	-4.8%	3.6%	-2.6%	0.1%	3.2%	-6.7%	3.2%	4.9%
2000	-2.4%	2.8%	-3.2%	5.2%	2.9%	2.2%	2.0%	5.1%	2.6%	-0.4%	-0.1%	5.2%
2001	-1.6%	0.2%	5.4%	-6.0%	1.5%	0.5%	0.0%	2.4%	8.6%	0.2%	-2.2%	-1.0%
2002	-2.8%	-2.8%	-1.1%	-3.8%	8.3%	10.0%	8.9%	-0.6%	2.8%	-4.5%	-1.4%	1.1%
2003	8.3%	4.6%	-8.8%	3.6%	8.6%	-1.4%	1.0%	2.8%	-2.9%	6.2%	2.4%	11.6%
2004	2.2%	3.3%	-1.4%	-3.3%	-2.5%	-1.2%	2.0%	-2.8%	2.8%	5.3%	12.0%	-0.8%
2005	-3.6%	1.1%	-2.0%	-2.8%	3.5%	2.4%	0.8%	0.3%	3.5%	-2.1%	4.9%	-2.3%
2006	5.5%	-0.5%	5.6%	5.3%	0.9%	-3.4%	-1.1%	2.0%	-0.9%	1.7%	7.2%	1.2%
2007	-3.1%	-2.2%	1.5%	6.5%	2.8%	2.2%	-4.0%	0.0%	9.1%	6.5%	2.1%	1.6%
2008	6.1%	16.8%	-5.0%	-0.6%	2.6%	0.0%	-4.3%	3.8%	8.8%	22.9%	0.4%	-1.3%
2009	-1.5%	1.3%	-5.0%	1.0%	10.1%	-5.6%	2.4%	-1.1%	3.7%	-0.5%	5.5%	-5.2%
2010	-4.2%	3.7%	-1.3%	0.0%	-1.3%	0.2%	0.7%	0.9%	5.2%	9.5%	-3.3%	4.0%
2011	1.2%	-0.4%	-3.3%	9.4%	-6.9%	-2.6%	2.4%	0.2%	5.1%	-9.6%	-1.0%	1.2%
2012	-1.6%	3.5%	-1.1%	-1.4%	2.0%	-7.9%	2.4%	-3.2%	-2.3%	-2.6%	-1.1%	6.1%
2013	4.5%	-2.6%	-1.0%	-0.8%	-0.8%	-1.6%	-0.8%	-3.5%	1.4%			

Table 13
Initial margin requirements in 2008

Initial margin requirements (IM) for a representative contract within each sector for the year 2008, obtained from the CME group. As data availability for margin requirements is limited, information about the non-agricultural sector could not be found. A new observation is shown when the IM, set by the exchange, changes. The first column presents the date when the IM is changed. The second column presents the IM, expressed in USD. The third column presents price quote. The fourth column presents the point value (the size of the futures contract, e.g. 50 kilos of corn), the fifth column presents the notional value of one contract in USD (price quote times point value). The sixth column presents the IM, expressed in percentage (IM expressed in USD divided by the notional value). The sample period runs from January to December 2008 (41 observations). The most extreme observation per contract is highlighted.

Agricultural (Corn)	IM	Price quote	Point value	Notional value (USD)	IM (%)
1/28/08	1350	502.3	50	25113	5.4%
3/27/08	2025	555.5	50	27775	7.3%
4/22/08	1350	607.8	50	30388	4.4%
6/9/08	1688	685.3	50	34263	4.9%
6/12/08	2025	739.5	50	36975	5.5%

Currency (AUD)	IM	Price quote	Point value	Notional value (USD)	IM (%)
1/2/08	1980	0.9	100000	87940	2.3%
1/17/08	6164	0.9	100000	87680	7.0%
2/28/08	1760	0.9	100000	94750	1.9%
3/18/08	1870	0.9	100000	91660	2.0%
3/25/08	1980	0.9	100000	90580	2.2%
5/16/08	1760	1.0	100000	95020	1.9%
7/17/08	1650	1.0	100000	96270	1.7%
7/30/08	1485	0.9	100000	93740	1.6%
8/13/08	1650	0.9	100000	87280	1.9%
9/4/08	2200	0.8	100000	82160	2.7%
9/24/08	2420	0.8	100000	83140	2.9%
10/1/08	6930	0.8	100000	78750	8.8%
10/2/08	2970	0.8	100000	77190	3.8%
10/9/08	3520	0.7	100000	69840	5.0%
10/10/08	4400	0.7	100000	65160	6.8%
10/17/08	7702	0.7	100000	69020	11.2%
10/20/08	5170	0.7	100000	69890	7.4%
10/30/08	9900	0.7	100000	67760	14.6%
11/11/08	12100	0.7	100000	65120	18.6%
11/26/08	4400	0.7	100000	65100	6.8%

Equity (Nikkei 225)	IM	Price quote	Point value	Notional value (USD)	IM (%)
1/23/08	4400	13095.0	5	65475	6.7%
10/1/08	4950	11600.0	5	58000	8.5%
10/17/08	5500	8655.0	5	43275	12.7%

Rate (Eurodollar)	IM	Price quote	Point value	Notional value (USD)	IM(%)
1/23/08	1980	97.1	2500	242688	0.8%
2/28/08	1760	97.1	2500	242725	0.7%
3/20/08	1870	97.8	2500	244375	0.8%
6/5/08	1540	97.2	2500	242900	0.6%
8/13/08	1430	97.0	2500	242488	0.6%
9/22/08	1100	96.8	2500	242000	0.5%
9/24/08	1650	96.3	2500	240750	0.7%
10/8/08	1210	97.1	2500	242838	0.5%
10/9/08	1760	97.1	2500	242638	0.7%
10/10/08	2200	97.1	2500	242863	0.9%
10/20/08	2530	97.5	2500	243700	1.0%
10/24/08	2970	97.4	2500	243513	1.2%
11/26/08	2750	97.9	2500	244863	1.1%

Figure 6
Margin to equity in 2008

Aggregated initial margin requirements divided by total equity value (M/E) for the year 2008 (260 observations). Initial margin requirements are calculated by multiplying the exposure by the most extreme intra-year initial margin requirement per sector (obtained from Table 13). Plotted is also the average M/E over the entire sample period January 1990 to September 2013.

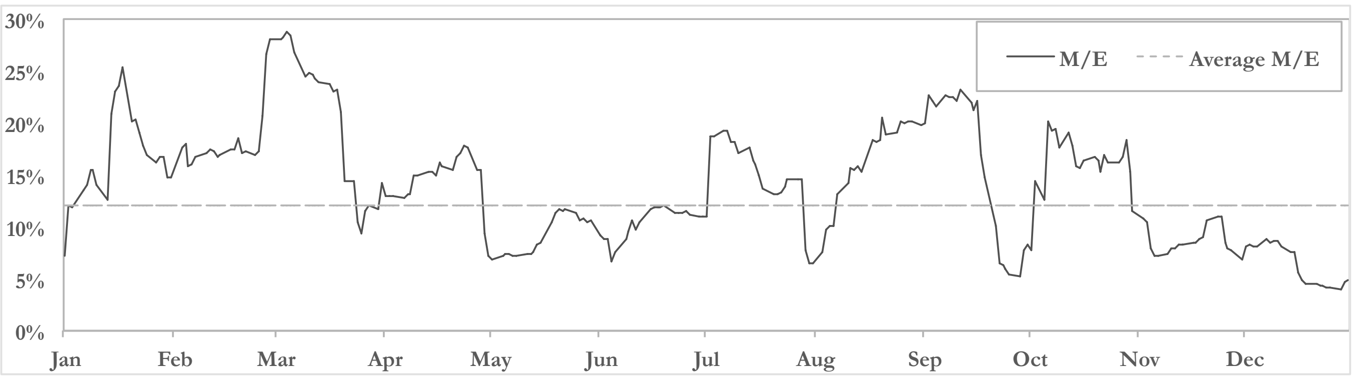


Table 14
Parameter stability

Robustness check for five of the main input parameters in the trend follow strategy. The input parameters risk, break-out window, trend-filter, stop/loss and ATR is altered by lowering the parameter one step and increasing the parameter one step from the original number. The shaded area represent the original numbers employed in the trend following strategy. The investment universe consists of 76 global futures contracts and the trading rules applied correspond to the break-out strategy. Return is based on total portfolio value and is net of trading costs. Volatility represents standard deviation and MDD is the maximum drawdown. Alpha - Pedersen factors is the intercept of the regression in Table 4. In Table 4, return of the trend following strategy above the risk free rate is the dependent variable and the long-short risk factors VAL EV, MOM EV and TS MOM are the independent variables. Autocorrelation and heteroskedasticity consistent Newey-West HAC t-statistics are reported in parentheses. The evaluated time period runs from January 1990 to December 2012 (276 observations). The alpha - CS Man Fut is the intercept of the regression in Table 6. In Table 6, the dependent the variable is the net of fees return of the trend following strategy above the risk free rate. The independent variable is the net return of the managed futures benchmark CS Man Fut above the risk free rate. The benchmark measures the aggregated performance of managed futures funds. Autocorrelation and heteroskedasticity consistent Newey-West HAC t-statistics are reported in parentheses. The evaluated time period runs from January 1990 to September 2013 (285 observations).

Parameter	**Risk (bp/contract)**			**Break-out window (days)**			**Trend-filter (days)**		
Unit	**6.5**	**7.5**	**8.5**	**15x30**	**25x50**	**50x100**	**25x50**	**50x100**	**75x150**
Mean return	1.063%	1.178%	1.295%	1.183%	1.178%	1.172%	1.060%	1.178%	1.162%
Volatility	3.524%	4.057%	4.593%	4.080%	4.057%	4.013%	4.768%	4.057%	3.852%
# of trades	6567	6567	6567	8579	6567	5925	8874	6567	6013
MDD	21.480%	24.808%	27.813%	28.926%	24.808%	25.452%	32.077%	24.808%	18.570%
Key metrics - Regressions									
alpha - Pedersen factors (equal to Table 4)	0.004**	0.004**	0.005**	0.005**	0.004**	0.004**	0.002	0.004**	0.004**
t-stat	(2.14)	(2.10)	(2.08)	(2.17)	(2.10)	(2.14)	(0.99)	(2.10)	(2.02)
alpha - CS Man Fut (equal to Table 6)	0.004**	0.005**	0.006**	0.005*	0.005**	0.005**	0.003	0.005**	0.006**
t-stat	(1.99)	(2.10)	(2.22)	(1.95)	(2.10)	(2.14)	(0.97)	(2.10)	(2.59)

Parameter	**Stop/loss (ATR units)**			**ATR (days)**		
Unit	**2**	**3**	**4**	**75**	**100**	**125**
Mean return	1.077%	1.178%	1.269%	1.202%	1.178%	1.162%
Volatility	3.386%	4.057%	4.418%	4.047%	4.057%	4.059%
# of trades	8410	6567	5758	6532	6567	6612
MDD	19.536%	24.808%	28.011%	23.817%	24.808%	24.353%
Key metrics - Regressions						
alpha - Pedersen factors (equal to Table 4)	0.004**	0.004**	0.005**	0.005**	0.004**	0.004**
t-stat	(2.56)	(2.10)	(2.10)	(2.26)	(2.10)	(2.05)
alpha - CS Man Fut (equal to Table 6)	0.005**	0.005**	0.006**	0.005**	0.005**	0.005**
t-stat	(2.34)	(2.10)	(2.25)	(2.24)	(2.10)	(2.07)

*p<=0.10, **p<=0.05, ***p<=0.01