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The relation between currency momentum and hedge fund returns

Navn: Jan Erik Lofnes Silden, Tor Arne Olsen

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by

Jan Erik Silden and Tor Arne Olsen

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ABSTRACT

In this thesis we are developing our own time series momentum factor to help explain the returns of currency trading hedge funds. We are also including both a time series momentum factor and cross-sectional momentum factors from the literature for a better comparison. We regress the hedge fund returns on each factor in addition to the well-known Fung & Hsieh factors to see how well the factors can explain these returns. Our findings indicate that the momentum factors explain the currency trading hedge fund returns well. We conclude that currency trading hedge funds do use currency momentum strategies to some extent.

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Chapter 1

Introduction

The momentum effect is one of the most researched topics in finance. Historically cross-sectional momentum has been studied the most. In the 1990s several papers started looking into time series momentum as a means of predicting a stocks future return using their own historical performance as a factor ((Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998)). In 2012 Moskowitz, Ooi and Pedersen (MOP hereafter) documented this effect across a wide variety of asset classes.

There has also been research on the relation between the return of commodity based hedge funds and a time series momentum strategy. Baltas and Kosowski (2013) found evidence which suggested that a time series strategy could explain a lot of the returns of commodity hedge funds. In addition, Hurst, Ooi and Pedersen (HOP hereafter) (2013) found that momentum strategies could explain a lot of the returns of both CTAs and Managed Futures funds. We want to see if this is also true for other hedge funds like those who trades currencies. For this we intend to use one of the HFR indices which focuses on currency trading hedge funds.

FX markets are more liquid and feature huge transaction volumes compared to equity markets. In this market, there are no short selling constraints that prevent professional investors to short past losers to fully implement momentum strategies. Hence, there is larger possibilities to generate significant excess returns from momentum strategies in FX markets compared to equity markets.

We develop our own momentum factor following the framework of MOP (2012) and Menkhoff et al.(2011). Based on the panel regression, we fail to identify return continuation or trends, in contrast to MOP (2012). The momentum factor that performs best over our sample period(1999-2019) is the 6-month formation, 1-month holding period in contrast to MOP (2012) which used 12-month formation. By analyzing our own developed momentum factor, we notice that the reason for the different use of formation periods is because of the difference in sample period. We also find clear indication of trends and momentum before the global financial crisis and none after.

Using Fung & Hsieh (2001) seven factor model as a basis for explaining hedge fund returns we expand the model with our own developed momentum factor. Additionally, we will examine the momentum factor(TSMOM) provided by MOP (2012) and the momentum factor(CSMOM) provided by Asness, Moskowitz and Pedersen (AMP hereafter) (2013). We run regressions of the hedge fund returns on the seven factors and then add the other factors one by one, so that there is no more than eight factors in the model at any time. Our findings indicate that the inclusion of another factor often increases the explanatory power of the linear regression model.

1.1 Research Question

We formulate a research question we want to answer in this thesis:

"Can a momentum strategy for currencies explain the returns of currency trading hedge funds?"

H0: A momentum strategy cannot explain the returns of currency trading hedge funds.

H1: A momentum strategy can explain the returns of currency trading hedge funds

1.2 Motivation and Contribution

We intend to provide some more research in this subject and hopefully share some new insight regarding the use of momentum strategies in hedge funds. With the findings from Baltas and Kosowski (2013) that Commodity Trading Advisors (CTAs) use time series momentum strategies in their asset management we believe that expanding on this work and seeing if similar strategies is employed by hedge funds who primarily trade in the foreign exchange market will be of great interest. Since Menkhoff, Sarno, Schmeling and Schrimpf (Menkhoff et al. hereafter) (2012) find a significant cross-sectional momentum effect and MOP (2012) find a time series momentum effect it makes sense to experiment with both kind of factors and see if either of the momentum strategies can help explain the returns of currency trading hedge funds.

Chapter 2

Literature Review and theory

Our thesis is related to three main topics of the literature: Momentum effects, currencies and hedge fund returns.

2.1 Momentum effect and Currencies

The first segment of literature our thesis relates to is time series momentum. We will look at time series momentum which was thoroughly analyzed by MOP (2012). MOP (2012) studied 58 different assets across 4 asset classes: commodities, equities, government bonds and currencies in the time period 1965-2010. They find that past excess return are a positive predictor of the future return and that the momentum effect persist for about a year, then partially reverses over longer periods. MOP(2012) construct a momentum factor for each asset class as well as a diversified momentum factor across all the different asset classes. This factor uses 12-month excess return as predictor of its future return, because it provided positive momentum profits not just on average but for every asset they examined. The paper also investigated the trading activity of speculators and hedgers in order to understand what drives the time series momentum. Some of the suggested explanations for why these strategies has provided abnormal returns is behavioural asset pricing theories, analyzed by Barberis, Shleifer and Vishny (1998) and Daniel, Hirshleifer, and Subrahmanyam (1998). Another possible explanation is growth related risk related to momentum winners as suggested by Liu and Zhang (2008). Limits to arbitrage is another example suggested by Chabot, Ghysels, and Jagannathan (2009).

Time series momentum is related to, but different from cross-sectional momentum which is analyzed by many papers (Jegadeesh and Titman 1993), (Jegadeesh and Titman 2001), (Pirrong 2005, Miffre and Rallis 2007), (Menkhoff et al. 2012). Jegadeesh and Titman (1993) found a significant cross-sectional momentum effect when they looked at the NYSE index from 1965 to 1989. They mention that one of the reasons might be under- and overreactions. Another possibility they comment on is that investors who buy past winners and sell past losers are making the prices overreact with their transactions. Other possible reasons was discussed in the wake of this paper, namely data mining and compensation for risk. In Jegadeesh and Titman (2001) they expand on their work with an out-of-sample test of their strategies which was consistent with their previous findings. This finding weakens the data mining argument, but the compensation for risk argument is still there. Recent papers such as Barroso and Santa-Clara (2015) show that a strategy similar to that of Jegadeesh and Titman would have lost -73.42% in just three months in 2009. However, a more diversified momentum strategy such as the global time series momentum strategy from MOP (2012) lost “only” 22% in their three worst months in 2009. Their momentum strategies for currencies also performed poorly in 2009, but not as bad as the equity markets.

The literature on currency momentum in time series of single exchange rates are often referred to as ”technical trading rules” which Menkhoff and Taylor (2007) surveyed. Menkhoff et al. (2012) studied 48 different currencies and considered the exchange rate against the USD. This paper found that there is an excess cross-sectional spread of up to 10% per year between past winners and losers. They found that transaction costs lower the excess return significantly, especially since a lot of the excess return is found in smaller currencies with higher bid-ask spreads. The spreads however, have had a tendency to decrease in the time period, in the paper they attribute this to the increasing prevalence of electronic broker services. With lower transaction costs the momentum strategy for currencies should work better, unless it is negated by more capital coming in to exploit this strategy, as is the case with many other strategies. Another explanation they point to is that the currencies with high idiosyncratic volatility and countries with high risk rating had the highest return. This is consistent with the arguments that the excess returns is compensation for these risks which is not captured by normal covariance risk measures.

While most literature find significantly positive excess returns using momentum strategies, Pukthuanthong-Le, Levich, and Thomas III (2007) argue that profits from following trends on foreign exchange rates have vanished. They look at all the major currencies from mid-1975 to mid-2006 and divide them into 3 subsections. They show that from late 1990s and forward, the trend following profits have vanished. The paper concludes that there are no longer possible to earn profits using moving average trend following rules in the most traded dollar currencies.

In the literature there has been documented several reasons for why prices under- and over-react. For under-reaction some of the theories are; anchoring, the disposition effect, non-profit seeking activities and slow moving capital. While for over-reaction the main theories are; herding, confirmation bias, fund flows and risk management. Figure 6.1 in appendix shows how the different theories fits within the life cycle of a trend.

Anchoring occurs when an assets price moves drastically away from a range it has been in for a while and investors buy the asset because they now believe it is under/overvalued based on its past price. The disposition effect is related to anchoring, but different in that it is based on the purchase price. Shefrin and Statman (1985) and Frazzini (2006) found that people sell winners too early and hold losers too long. The implications from this is that winning assets will have downward pressure from people seeking to realize their gains. Losing assets however, won't drop to their fundamental value immediately because of hesitant sellers.

Perhaps the most relevant explanation for currencies is the fact that central banks operate in the currency and fixed income markets. Their goal is to reduce exchange-rate and interest-rate volatility. According to Silber (1994) this might slow down the price adjustment to news. Duffie (2010) suggests that slow moving capital can help explain why price discovery can take some time. He describes a situation where supply and demand shocks will cause a price shock followed by an extended reversal process.

The herding effect, or the bandwagon effect happens when investors buy an asset just because it has been performing well for a while and the fact that other investors have bought it. It can happen in individual stocks, or in whole sectors, like the dot-com bubble between 1995-2000. The best example recently is perhaps the Bitcoin's rise and fall in 2017-2018.

Wason (1960) and Tversky and Kahneman (1974) showed that people look for information which confirms what they already believe. An extension of this is that they view recent price moves as representative for the future returns. This leads to investors moving capital from underperforming investments into over performing investments and strengthening the trend.

Studies have also shown that fund investors "chase" performance (Benogni et.al. 2000). By investing in the funds who have performed well in the past, the funds obtain more money. The funds place that money into the same assets, contributing to an increase in the price of those assets. A similar effect also happens for the underperforming funds, who see their investors withdrawing money from the funds, and therefore creating more downwards pressure on the prices. In addition, some risk management strategies will only hedge when the currency or commodity reaches a certain level. For example an exporting firm might want to hedge foreign exchange exposure after the currency have moved against them, to prevent further pressure on the margins. This type of risk management can create a feedback loop according to Garleanu and Pedersen (2007).

2.2 Hedge Funds

The second part of our thesis is based on research by Fung & Hsieh which in several papers have studied how to evaluate hedge fund performance. Fung & Hsieh (2004) propose seven factors in a linear factor model which is explaining a lot of the returns obtained by hedge funds. The trend following factors are constructed based on the article Fung & Hsieh (2001). They argue that a lot of hedge fund strategies have option like returns, and that traditional factors are having difficulty explaining these returns. They introduce three Primitive Trend Following Strategies (PTFS) which should help explain the hedge fund returns. Together with four more traditional factors (Equity market factor, size spread factor, bond market factor and credit spread factor) they propose the seven factor model which is still used today when evaluating hedge fund performance.

In Baltas and Kosowski (2013) they showed that a time series momentum strategy could explain a lot of the returns gained by commodity hedge funds in the Commodity Trading Advisor (CTA) index, although CTA is a misleading description since these funds can trade virtually anything. They base their work on the methodology from MOP (2012) and extend the work by seeing how well time series momentum strategies can explain CTA fund returns. They found that the momentum strategies are highly significant even when they control for the Fama and French (1993) factors and the Fung & Hsieh (2001) factors.

In Demystifying managed futures (HOP 2013) they look for time series momentum returns in a wide variety of assets. For currencies they use forward contracts to show that time series momentum strategies can provide excess returns here as well. In addition, they show that these strategies can explain a lot of the returns obtained by Managed Futures funds and CTAs. In the paper they also discuss a few of the reasons why trends exist and how they are formed.

By creating time series momentum strategies and comparing it with the returns from a CTA index and Managed Futures index both papers find that factor models with a time series momentum factor explains a lot of the returns obtained by these hedge funds. It is already known that currencies show signs of time series momentum (MOP 2012) and cross-sectional momentum (Menkhoff et al. 2012).

MOP (2012), Baltas and Kosowski (2013) and HOP (2013) all find that a large part of the hedge fund industry follows time series momentum strategies. These studies look at managed Futures funds and commodity trading advisors (CTAs). Our contribution to this field of study is that we create a time series momentum factor similar to MOP (2012) and see if it can help explain the returns of hedge funds who primarily trade currencies. Additionally, we also experiment with the currency momentum factor from MOP (2012) and AMP (2013) to see if similar momentum factors can help explain hedge fund returns.

2.3 Risks and Constraints in Hedge Funds

Standard deviation is the most common risk measure and represent the volatility of returns measured in percentage. Usually, when comparing funds with identical annualized returns you can look at the standard deviation, and choose the most attractive (the fund with the lowest standard deviation). In hedge funds however, standard deviation does not capture the total risk of returns. Standard deviation assumes a bell-shaped distribution, and hedge funds do not have normally distributed returns. A bell-shaped distribution assumes that the probability of returns above the mean is the same as the probability of returns is below the mean. Most hedge fund returns are usually skewed in one or the other direction, which means that the distribution is not comparable to the bell-shaped distribution. This is based on Fung & Hsieh (1999), who finds that hedge fund returns are leptokurtic or fat-tailed.

Leverage is one of the main reasons why hedge funds incur huge losses. Any negative return effect gets worse as the leverage of the hedge fund increases. This causes hedge funds to sell assets at discounts to cover margin calls. Consequently, hedge funds with more debt have in some cases been driven out of business due to the leverage effect.

Liquidity is another example of a risk related to hedge fund. Liquidity refers to how quickly assets can be converted to cash. Many hedge funds require a lock up period of 1-3 years, and this can block possible liquidity opportunities. Additionally, hedge funds often offer a strategy of investing in a restricted sector for enhancing the returns. This concentration risk can be conflicting to investors who expects broad diversification in various sectors.

Hedge funds trading with currencies also gets exposed to exchange rate risk. An investments value can change due to fluctuations in the value of the different currencies. When closing out positions in foreign currency, investors also face exchange rate risk because of the same reason.

Chapter 3

Methodology

We construct our momentum factor by following the framework of MOP (2012) and Menkhoff et al. (2012). Time series momentum look at past returns on its own security and try to determine whether the asset will go up or down in the consecutive period. A positive past return is considered a positive trend and leads to a long position and negative past returns leads to a short position, identical to other papers. Similar to MOP (2012), we look at different trading strategies by varying the look-back period and keeping the holding period constant with monthly re-balancing. The look-back period is intuitively the past returns we look at to signal which position to take and the holding period the number of periods we hold the strategy. By looking at different trading strategies we can determine which strategy performs best over our sample period.

3.1 Constructing factors

3.1.1 Construction of Excess Returns

Similar to Menkhoff et al. 2012, we define the excess returns as ex post deviations from the uncovered interest parity, i.e

$$rx^k_{t+1} = i^k_t - i_t - \Delta s^k_{t+1}$$

where rx^k_{t+1} represent the excess return for currency k in period t+1. i^k_t is the short term interest rate in country with currency k, i_t its home country, in our case the US. Δs^k_{t+1} is the change in the log spot exchange rate of currency k relative to the home currency(in our case USD). When s increases, it correspond to an appreciation of the home currency or a depreciation of the foreign currency.

We compute excess returns at the monthly frequency, where the covered interest parity usually holds (Akram et al. 2008). Consequently, interest rate differentials are approximately equal to the forward discount.

$$i_t^k - i_t \approx f_t^k - s_t^k$$

Here, f_t^k represent the log forward exchange rate at time t. Based on these equation, we can write the log excess returns as the difference between log forward discount and the log spot rate changes

$$rx_{t+1}^k = (f_t^k - s_t^k) - \Delta s_{t+1}^k$$

This equation is equivalent to buying currency k in the forward market and selling it (in our case) one month later in the spot market

$$rx_{t+1}^k = f_t^k - s_{t+1}^k$$

This will be the log monthly excess return to a US investor for holding currency k. The reason for using forwards instead of spot data is that spot rates are only one component of the profit and loss on a trade that involves currencies. It is important to consider the interest received on the long currency and the funding cost of the short currency when calculating profits. Forward market prices do this automatically.

Summary of the descriptive statistics on the excess returns are presented in table 6.1 in appendix. The two columns shows the time series mean and the standard deviation(annualized) of each of the 7 currencies we look at. In contrast to MOP (2012), which investigates several different asset classes, we only look at currencies. Consequently, we have not volatility scaled the returns of the currencies because the volatility is similar across the different currencies.

Another part of the theory we do not consider is the bid-ask spread. The reason for it is because we only look at the major currencies against the USD. These currencies feature huge transaction volume, and will as a result have very tight bid-ask spreads.

3.1.2 Trend identification

We will examine time series predictability by focusing on the sign of the past excess return. The strategy can be captured by the following regression:

$$r_t^k = \alpha + \beta_h sign(r_{t-h}^k) + \epsilon_t^k$$

where the excess return in currency k at time t r_t^k is regressed on the sign of the past h excess returns in currency k $sign(r_{t-h}^k)$. We run a pooled panel regression and report the t-statistics for the β in Figure 6.3 in appendix. Here we look for patterns like return continuation or trends and reversals.

3.1.3 Trading strategies

Similar to MOP (2012) we determine the TSMOM return for any currency like this:

$$r_{t,t+1}^{TSMOM,k} = sign(r_{t-h,t}^k) \cdot r_{t,t+1}^k$$

where the past excess returns over h months determine whether you go long(sign=1) or short(sign=-1) the next month in currency k. This will determine your excess return in period t when investing in currency k. We compute the TSMOM return for each available month from 1999 to March 2019, depending on the formation period used. When determining the formation period used to create the momentum factor, we will use the one with the highest annualized return over the sample period.

3.1.4 Momentum factor construction

Using this methods, we will be able to construct a momentum factor, similar to the one constructed in MOP (2012). First, we look at each currency separately and then pool all the currencies together in a diversified portfolio. We form an equal weighted portfolio to represent our momentum factor. The different momentum factors is presented as graphs of cumulative returns in figure 6.2 in appendix.

3.2 Regression Analysis Methodology

We describe how we are conducting our regression analysis and what we are looking for.

3.2.1 Linear Regression Model

In our analysis we will be using linear factor models to try to explain hedge fund returns. The seven factor model developed by Fung & Hsieh will be used as a basis. We will then expand on this model with various momentum factors to see if this helps us explain hedge fund returns.

$$R_t - r_{f,t} = \alpha + \beta_1 PTFS - Bond_t + \beta_2 PTFS - Curr._t + \beta_3 PTFS - Comm._t$$
$$+ \beta_4 EquityMarket_t + \beta_5 EquitySpread_t + \beta_6 BondMarket_t + \beta_7 Creditspread_t + \epsilon$$

By running the shown regression we obtain coefficients and t-stats for the different factors. This enables us to see how much of the hedge fund returns can be explained by these factors. We will combine different factors to see which ones are best suited to explain the returns of the three different hedge fund indices we are looking at.

Chapter 4

Data

Our data covers the period from February 1998 to March 2019 for the global Hedge Fund index and the macro hedge fund index. Currency hedge fund index is only available from January 2005. Consequently, we only use factor returns from February 1998 to March 2019 when analyzing global- and macro index and January 2005 when analyzing currency index. When analyzing our own factor the time period is from July 1999 to March 2019, due to 6-month look-back period and the existence of Euro. While a longer time period would be ideal, especially when considering momentum strategies with longer look back periods, we believe approximately 20 and 14 years of monthly data should enable us to draw meaningful conclusions.

4.1 Hedge Fund Returns

We are using three different hedge fund indices in our thesis. They are made by Hedge Fund Research (HFR) and obtained from Bloomberg. The strategies are asset weighted based on the distribution of assets in the hedge fund industry. HFR utilizes a UCITSIII compliant methodology to construct the HFRX Hedge Fund Indices. The methodology is based on defined and predetermined rules and objective criteria to select and rebalance components to maximize representation of the Hedge Fund Universe. HFRX Indices utilize state-of-the-art quantitative techniques and analysis; multi-level screening, cluster analysis, Monte-Carlo simulations and optimization techniques to ensure that each Index is a pure representation of its corresponding investment focus. Below is a short description from the HFR website for each of the indices we use. The hedge fund returns are reported net of all fees and the fund returns are denominated in USD.

4.1.1 Global Hedge Fund Index

The HFRX Global Hedge Fund Index is designed to be representative of the overall composition of the hedge fund universe. It is comprised of all eligible hedge fund strategies; including but not limited to convertible arbitrage, distressed securities, equity hedge, equity market neutral, event driven, macro, merger arbitrage, and relative value arbitrage.

4.1.2 Macro Hedge Fund Index

Macro strategy managers trade a broad range of strategies in which the investment process is predicated on movements in underlying economic variables and the impact these have on equity, fixed income, hard currency and commodity markets. Managers employ a variety of techniques, both discretionary and systematic analysis, combinations of top down and bottom up theses, quantitative and fundamental approaches and long and short term holding periods. Although some strategies employ RV techniques, Macro strategies are distinct from RV strategies in that the primary investment thesis is predicated on predicted or future movements in the underlying instruments, rather than realization of a valuation discrepancy between securities. In a similar way, while both Macro and equity hedge managers may hold equity securities, the overriding investment thesis is predicated on the impact movements in underlying macroeconomic variables may have on security prices, as opposed to EH, in which the fundamental characteristics on the company are the most significant and integral to investment thesis.

4.1.3 Currency Hedge Fund Index

Currency Index include both discretionary and systematic currency strategies. Systematic Currency strategies have investment processes typically as function of mathematical, algorithmic and technical models, with little or no influence of individuals over the portfolio positioning. Strategies which employ an investment process designed to identify opportunities in markets exhibiting trending or momentum characteristics across currency assets classes, frequently with related ancillary exposure in sovereign fixed income. Strategies typically employ quantitative process which focus on statistically robust or technical patterns in the return series of the asset, and typically focus on highly liquid instruments and maintain shorter holding periods than either discretionary or mean reverting strategies. Although some strategies seek to employ counter trend models, strategies benefit most from an environment characterized by persistent, discernible trending behavior. Systematic Currency strategies typically would expect to have greater than 35% of portfolio in dedicated currency exposure over a given market cycle. Discretionary Currency strategies are reliant on the fundamental evaluation of market data, relationships and influences as they pertain primarily to currency markets including positions in global foreign exchange markets, both listed and unlisted, and as interpreted by an individual or group of individuals who make decisions on portfolio positions; strategies employ an investment process most heavily influenced by top down analysis of macroeconomic variables. Portfolio positions typically are predicated on the evolution of investment themes the Manager expect to materialize over a relevant time frame, which in many cases contain contrarian or volatility focused components. Investment Managers also may trade actively in developed and emerging markets, focusing on both absolute and relative levels on equity markets, interest rates/fixed income markets, currency; frequently employing spread trades to isolate a differential between instrument identified by the Investment Manager to be inconsistent with expected value. Discretionary Currency strategies typically would expect to have greater than 35% of portfolio in dedicated currency exposure over a given market cycle.

4.1.4 Descriptive Statistics Hedge Funds

Table 4.1: **Descriptive Statistics Hedge Funds**

This table shows the performances of the Hedge Fund Indices net of fees and the risk free rate.

Hedge Fund	Data start date	Ann. Mean	Ann. Vol.	Skew.	Excess Kurt.	SR
Global	Feb-98	2.34%	5.86%	-0.74	5.60	0.40
Macro	Feb-98	2.42%	7.70%	0.30	2.11	0.31
Currency	Jan-05	-0.94%	4.34%	-0.36	1.54	-0.22

From the table we see that the Global and Macro Index are delivering decent returns. The Currency Index does however have an annualized return of -0.94% which is quite poor. It is important to note that these returns are after all fees and excess of the risk free rate. According to HOP (2013) the time series momentum strategy would have about 6% annual fees on average with a 2-and-20 fee structure. If the hedge fund indices are somewhere close to this amount of fees then it is rather impressive that two out of three are able to provide positive excess returns.

Another difference between the three indices is that the Global and Macro funds are covering about seven years more than the Currency Index. If the bulk of positive returns where obtained in this period then that could explain why the Currency Index is performing worse. This seems like it is the case, as shown in figure 4.1 below. Here we can see that in the period from 1998 to 2005 the Global and Macro funds more than doubles, while the increase has been flatter in the period after. Since we don't have data from the Currency Index from before 2005 we can not say if this index would have a similar increase in that time period.

4.2 Factors

We will be using a variety of factors from the research on this subject. In the literature that aims to explain hedge fund returns the 7 factor model from Fung & Hsieh(2001) is the workhorse model. Since we are aiming to explain the returns of currency trading hedge funds we will incorporate different currency momentum factors to shed some light on how the returns are obtained. We developed our own momentum factor that we use to explain hedge fund returns. Additionally, we use the Time Series Momentum Factor from MOP(2012) and the Cross Sectional Momentum Factors from AMP(2013). The factors will be described in further detail in the following sections.

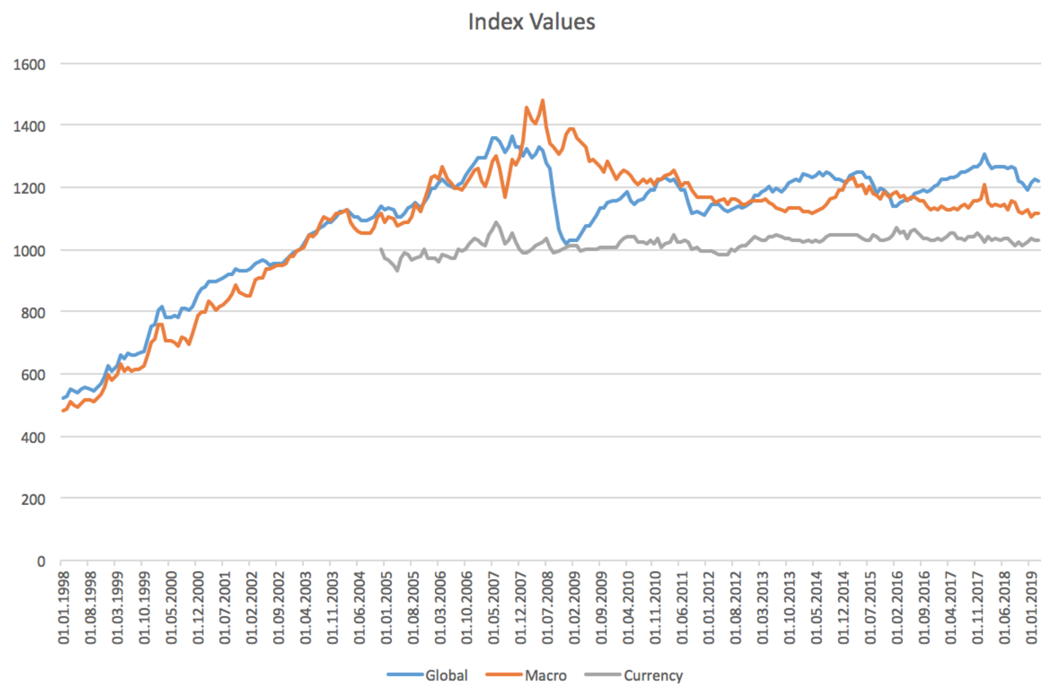

Figure 4.1: **Hedge Fund Index Values**

4.2.1 7 Factor Model

The 7 factors in Fung & Hsieh is:

- Bond, Currencies and Commodities Trend-Following Factors
- The Equity Market Factor
- The Equity Size Spread Factor
- The Bond Market Factor
- The Credit Spread Factor

Trend-Following Factors

The three trend-following factors on bonds, currencies and commodities were presented in Fung & Hsieh(2001) and is called Primitive Trend-Following Strategies(PTFS). The empirical returns of the strategies is created using look-back straddles. For bonds they used futures contracts on the U.S. 30-Year Treasury Bonds, UK Gilts, German Bunds, the French 10-year Government Bond and the Australian 10-year Government Bond. For currencies they used futures contracts on the British pound, Deutsche mark, Japanese yen, and Swiss franc. For commodities they used futures contracts on soybean, corn, wheat, gold, silver and crude oil.

The Equity Market Factor

The Equity Market Factor is represented by the S&P 500 Monthly Total Return Index. This captures the returns including dividends from 500 large cap companies in the US. The S&P 500 is often used in factors that wants to capture the market risk due to the covering of a wide array of sectors and a fairly large amount of companies. The large amount of funds are exposed to equity market risk, this means that the Equity Market Factor and the Equity Size Spread Factor are the two major risk factors for a lot of the funds.

The Equity Size Spread Factor

In the paper they used Wilshire Small Cap 1750 monthly return minus the Wilshire Large Cap 750 monthly return. The factor they use now is the Russell 2000 Monthly Total Return Index minus the S&P 500 Monthly Total Return Index. By taking the small cap return minus the large cap return you get a factor which is similar to the SMB factor in Fama & French's three factor model. The argument for this factor is that over time, the performance of smaller companies should be better than the market as a whole.

The Bond Market Factor

The Bond Market factor is represented by the monthly change in the 10-year Treasury Constant Maturity Yield. This factor, along with the credit spread factor are the main factors for explaining Fixed Income Hedge Fund returns. These funds are often exposed to interest rates and the spreads between different interest rates, explained further in the Credit Spread Factor.

The Credit Spread Factor

As a Credit Spread Factor they used monthly changes in Moody's Baa Yield minus the monthly change in the 10-year Treasury Constant Maturity Yield. This factor is much like the Equity Size Spread factor but instead it captures the spread between moderate credit risk bonds and the 10 year risk free rate. In their paper, Fung & Hsieh argues that this factor is good at explaining the risks that are common for Fixed Income

Arbitrage Hedge Funds. These funds often buy bonds with lower credit ratings and hedge the interest rate risk by shorting treasuries. In addition these funds are often leveraged, and thus susceptible to the liquidity of the bond market place. This is also captured in the credit spread.

4.2.2 Our own factor

The factor we have constructed are replicated by the use of similar methods as MOP(2012) and Menkhoff et. al (2012). The currency pairs included in our portfolio are the most traded currencies similar to MOP (2012), without the addition of Swedish krona and Norwegian krone. In contrast to MOP (2012) and AMP (2013), our factor is not volatility scaled. Based on the sample period from 1999-2019 and the construction method, we use 6-month formation period and 1-month holding period.

4.2.3 Time Series Momentum Factor MOP

In MOP(2012) they use 12 cross-currency pairs from nine underlying currencies to develop a Time Series Momentum Factor for currencies. In the paper they use currency data from 1971-2009, which means their sample period differs quite a bit from our constructed factor. The factors in MOP are volatility scaled so that they can make meaningful comparisons across asset classes. They are using a 12-month formation period and 1-month holding period since this is the most used momentum period in the literature. Each asset is looked at individually and then pooled together into a diversified momentum factor. They construct time series momentum factors for the equity market, the fixed income market, the commodity market and the currency market. Since we are focusing on currencies we will only be using that factor in our analysis.

4.2.4 Cross-Sectional Momentum Factor AMP

In this paper they are using currency data from 1979 to 2011. The currency pairs used in the Cross-Sectional Momentum Factor from AMP (2013) are largely the same as the ones used in MOP(2012) with the addition of the Swedish krona and the Norwegian krone. They compute three different momentum portfolios from a low, middle and high quantile. Similar to MOP(2012), the factors in this paper is also volatility scaled. The difference between these factors is that they base their actions on the currencies performance relative to the average of the currencies, while a time series strategy would only look at the currencies own past performance.

4.2.5 Descriptive Statistics Factors

Table 4.2: **Descriptive Statistics Factors**

This table shows the performances of the factors from February 1998 to March 2019. 6MTSM is from July 1999. We present Annualized Volatility and Mean, Skewness, Excess Kurtosis and the Sharpe Ratio.

Factor	Ann. Mean	Ann. Vol.	Skew.	Excess Kurt.	SR
Fung & Hsieh Factors					
PTFS-Bond	-23.06%	52.58%	1.34	2.40	-0.47
PTFS-Curr.	-10.39%	64.23%	1.24	1.85	-0.19
PTFS-Comm.	-8.02%	49.40%	1.18	1.94	-0.20
Eq. Market	5.90%	15.31%	-1.06	2.41	0.26
Eq. Spread	-0.45%	11.08%	-0.11	4.07	-0.21
Bond Market	-7.51%	28.58%	-0.64	2.62	-0.32
Credit Spread	5.05%	22.98%	0.67	2.65	0.14
Our own factor					
Factor	Ann. Mean	Ann. Vol.	Skew.	Excess Kurt.	SR
6MTSM	2.00%	6.18%	0.33	2.26	0.05
Other factors from the literature					
Factor	Ann. Mean	Ann. Vol.	Skew.	Excess Kurt.	SR
TSMOM	9.33%	17.33%	0.49	2.31	0.42
CSMOM1	-0.42%	8.50%	0.07	3.12	-0.27
CSMOM2	1.31%	7.98%	-0.10	1.23	-0.07
CSMOM3	1.20%	8.29%	-0.06	1.66	-0.08

The Fung & Hsieh factors seems to have a lot higher volatility on average, while the returns of those factors are very variable. The PTFS factors are delivering very poor returns in the period we are looking at with returns between -8% and -23%. The only factor providing positive returns are the Equity Market Factor and the Credit Spread Factor. These deliver annualized returns of 5.90% and 5.05% respectively. While this is solid numbers on its own, the Sharpe ratios of the factors is only 0.26 and 0.14 which is not very impressive numbers.

Our own 6MTSM factor has an annualized mean of 2.00% with a very low volatility of 6.18%. The Sharpe ratio is however, just barely positive, with 0.05. If we compare it to the TSMOM factor from MOP, that one has about three times higher volatility and more than four times higher return. In that sense, this factor is quite similar with the exception of this one not being scaled to a higher volatility. Our factor is also using a bit fewer currency pairs, which might also impact the return and volatility.

The TSMOM factor is by far the best performing factor in terms of returns and Sharpe Ratio. With annualized returns of 9.33% and a Sharpe ratio of 0.42 it is outperforming all the other factors. Although these returns are quite impressive, it would be hard to achieve similar results in real life as these returns are gross of transaction costs and any management fees. The transaction costs for a momentum strategy is estimated to be between 1-4% per year for a sophisticated manager, and possibly much higher for less sophisticated traders (HOP 2013). The historical transaction costs for the momentum strategies is not known, and therefore there is uncertainty related to these numbers. Regardless, it is clear that the net returns would be less than 9.33% annually over a longer time period.

While the TSMOM factor is providing excellent returns the CSMOM factors are showing relatively low returns and volatility. With annualized means between -0.42% and 1.31% this is below the risk free rate for the period, leading to negative sharpe ratios for all three CSMOM factors. In AMP (2013) the CSMOM 1 and 2 factors are delivering poor returns of -0.7% and 0.3% while CSMOM 3 has 2.8% in the same time period. For the time period we are looking at the numbers are in the same range with the CSMOM 2 slightly surpassing CSMOM 3.

4.2.6 Correlations among factors

Table 4.3 shows the pairwise correlations between the different factors. If different factors are highly correlated we can get problems with multicollinearity in our regression model. This in turn, can make factors appear insignificant when they should be significant because it increases the standard error of the coefficients. When this happens we might arrive at the wrong conclusions.

From the table we can see that the Credit Spread factor is highly negatively correlated with the Bond Market factor. This seems reasonable since the Credit Spread factor is just the Moody's Baa Yield minus the Bond Market factor. An increase in the Bond Market factor would therefore lead to a decrease in the Credit Spread factor unless the Baa Yield changes accordingly.

Other notable correlations is those between the Cross-Sectional Momentum factors and the one between TSMOM and 6MTSM. The Cross-Sectional Momentum factors have correlations of 0.750, 0.523 and 0.754. This seems natural since they are just low, middle and high quantiles of the same momentum strategy. The TSMOM and 6MTSM factors have a correlation of 0.555 in the period. They are based on the same currency pairs so this could be one of the reasons why they are so correlated. Because of these rather high correlations we are adding the factors one by one in our regressions.

Table 4.3: **Factor Correlation Matrix**

This table shows the correlation between the different factors from July 1999 to March 2019.

	PTFSBond	PTFSCurr	PTFSCom	EqMkt	SizeSpread	BondMkt	CreditSpread	TSMOM	CSMOM1	CSMOM2	CSMOM3	6MTSM
PTFSBond	1											
PTFSCurr	0.362	1										
PTFSCom	0.153	0.336	1									
EqMkt	-0.240	-0.256	-0.192	1								
SizeSpread	-0.061	0.034	-0.025	0.173	1							
BondMkt	0.035	0.017	-0.004	0.225	0.112	1						
CreditSpread	0.002	0.046	0.041	-0.314	-0.107	-0.916	1					
TSMOM	0.063	0.211	0.132	-0.069	-0.056	-0.029	0.033	1				
CSMOM1	-0.099	-0.062	-0.056	0.391	0.098	0.154	-0.225	-0.372	1			
CSMOM2	-0.096	-0.026	-0.030	0.407	0.127	0.140	-0.218	0.026	0.750	1		
CSMOM3	-0.150	-0.010	0.041	0.340	0.081	-0.018	-0.050	0.296	0.523	0.754	1	
6MTSM	0.000	0.228	0.144	-0.147	-0.066	-0.158	0.183	0.555	-0.217	0.067	0.240	1

Chapter 5

Analysis

Figure 6.2 in appendix shows our momentum strategies for look-back periods of 1,3,6 and 12 months. The figure shows that based on our sample period, the 6-months look- back period performs best. Consequently, we have used this look-back period when determining our momentum factor. The MOP (2012) factor uses 12-months look back period based on a different sample period. Their sample period stops in 2009, and we can see similar results as MOP (2012) if only looking at the figure until 2009. When looking at the strategies pre-crisis(-2009) we see that the 12-month look back period strategy outperforms the other quite significantly. We also acknowledge that all the strategies are increasing during these years. Examining the strategies during the crisis in 2008, it seems like the largest returns from the momentum strategies appears when the market experiences large up and down movements. This is consistent with the findings of MOP (2012). Post-crisis we see that most of the momentum effect disappears for all the strategies and the cumulative return isn't increasing like pre-crisis.

Figure 6.3 in appendix shows us the t-values for each month lag, from a pooled panel regression. In contrast to MOP (2012) findings, we fail to identify significant return continuation or trends. The only statistically significant t-value the first 12 months, is 6-month lag(positive) and 7-month lag(negative). This is connected to the sample period issue we identified when determining the formation period. As mentioned, we saw clear indication of trends in figure 6.2. One half of our sample (pre-crisis) indicates trends, while the other half(post-crisis) indicates more consistency with the random walk theory in whether the past performance can predict future performance.

Figure 5.1: **6MTSM vs Global Hedge Fund Index**

Figure 5.1 shows the cumulative return of the constructed 6MTSM factor and the Global Hedge Fund Index. We see that by the start of 2000s, when hedge fund gained popularity worldwide, the cumulative return of the Global hedge fund index increased quite significantly. The Global Hedge Fund Index took a big hit during the global financial crisis in 2008, and the index suffered huge losses as indicated by figure 5.1. The following years after the crisis the Global Hedge Fund Index increases its cumulative return slightly compared to before the crisis. The biggest difference between the cumulative returns are definitely the global financial crisis. Where the Global Hedge Fund Index incur huge negative returns, the 6MTSM factor performs much better and incur positive returns. The reason for this is that the Global Hedge Fund Index includes stocks, which the 6MTSM does not.

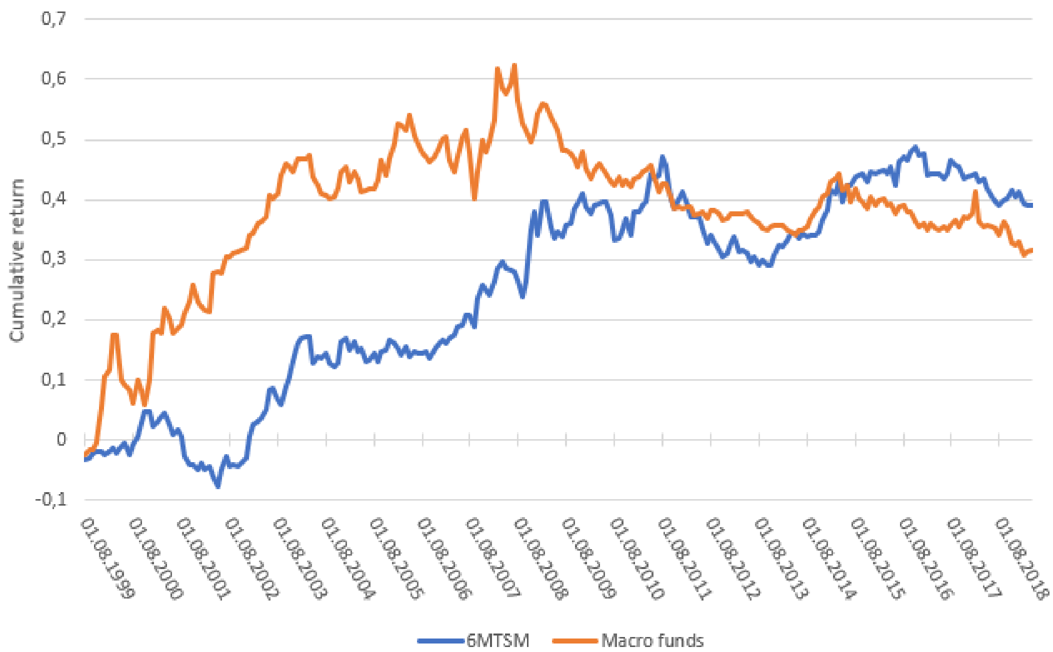

Figure 5.2: **6MTSM vs Macro Hedge Fund Index**

Figure 5.2 shows the cumulative return of the constructed 6MTSM vs the Macro Hedge Fund Index. The same pattern appears here, except that the Macro Hedge Fund Index does not incur huge negative returns during the global financial crisis as expected. The cumulative returns follows the same pattern until the crisis. Also in this figure we notice that the there seems to be a trend before the crisis, while after the crisis the Macro hedge funds cumulative return decreases. This is consistent with the findings of Pukthuanthong-Le, Levich, and Thomas III (2007), who argues that the profits of certain technical trading rules often tend to deteriorate over time as more traders learn about the strategies and start to exploit them.

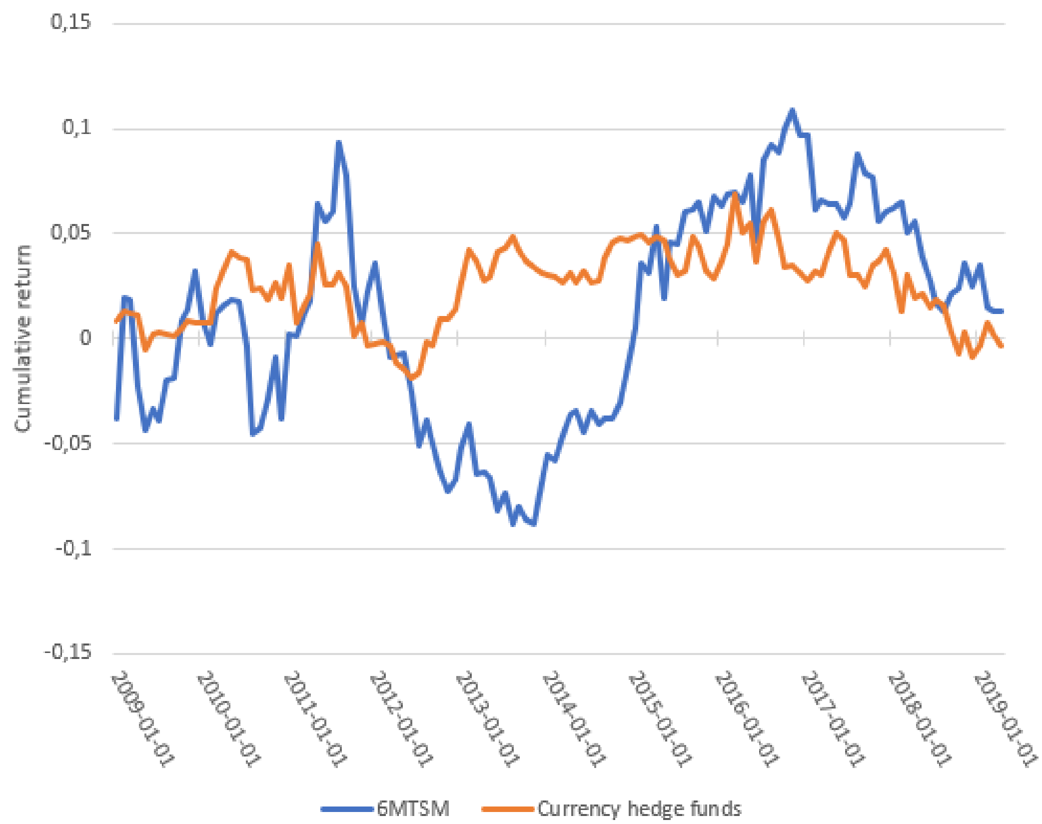

Figure 5.3: **6MTSM vs Currency Hedge Fund Index**

Figure 5.3 shows the cumulative return of the constructed 6MTSM factor vs the Currency Hedge Fund Index. The excess returns of the Index has not been positive over the sample period. To get a better visual comparison between the two returns, we have chosen to only look at post crisis. We notice that while the Currency Index is more stable the last 10 years, the 6MTSM factor cumulative returns varies more. This is probably due to the fact that a Currency Index trades all kinds of currencies, while the 6MTSM factor only includes the most traded currencies. If the Currency Index uses momentum strategies, the strategies will be more diversified than the 6MTSM. Hence, the 6MTSM factor will vary more in the cumulative returns than the Currency Index cumulative returns.

5.1 Regression Results

5.1.1 Seven Factor Model and our own factor

In table 5.1 we show the results of a regression of our constructed 6MTSM factor in addition to the Fung & Hsieh factors on excess hedge fund returns. Firstly we see that the beta is significantly different from zero on a 95 % level for both the Macro- and the Currency hedge fund. The factor is significant on a 90 % level for the Global index with a t-stat of 1.88. This makes sense because the Global Hedge Fund Index includes the Macro and Currency hedge funds as well as many other hedge funds.

Looking at the intercept/alphas we see that it decreases for both the Global index and the Macro funds. This indicates that the factor is explaining the excess return of the index/funds to some extent. The adjusted r-squared is also improving for these two regressions, strengthening our indication that the factor does explain the excess return. The effect the factor has on the Global index excess returns is explaining only a small part of the returns as expected because this is a global index, and this strategy will only be possible to implement by hedge funds trading currencies.

The 6MTSM factor has a positive correlation to the excess returns on Macro funds. The coefficient is 26.83 % which indicates that when the 6MTSM factor increases by 1 %, the excess return on the macro funds increase by 26.83 %. We also see that for the currency fund the adjusted r squared increases and the coefficient is 8.01 %. This combined with the fact that the coefficient is significant on a 95 % level indicates that momentum strategies is used in currency hedge funds. The alpha however is negative because the currency hedge funds does not give abnormal returns after adjusting for the benchmarks.

Table 5.1: **Seven Factor Model and our own factor**

Panel A shows the results from regressing the three hedge fund index returns (The Global Hedge Fund Index returns, the Macro Hedge Fund Index returns and the Currency Hedge Fund Index returns) on the seven Fung & Hsieh factors. Bond, currencies and commodities trend-following factors, the equity market factor, the equity size spread factor, the bond market factor and the credit spread factor. Panel B shows the regression including our own factor which is the constructed 6MTSM factor. The number in parentheses are the t-stat. The time period is from July 1999 to March 2019 for the Global and Macro Index, and January 2005 for Currency index.

	PTFSBond	PTFSCurr	PTFSCom	EqMkt	SizeSpread	BondMkt	CreditSpread	6MTSM	Intercept (Alpha)	Adj. R-Sq
Panel A: Seven Factors										
Global	-0.03 %	-0.01 %	-0.02 %	7.37 %	2.89 %	-0.06 %	-0.33 %		0.01 %	0.402
	(-0.48)	(-0.09)	(-0.33)	(9.05)	(4.53)	(-0.18)	(-1.01)		(1.28)	
Macro	0.19 %	0.17 %	0.30 %	1.74 %	1.80 %	0.07 %	0.06 %		0.03 %	0.063
	(1.45)	(1.60)	(2.20)	(2.49)	(2.06)	(0.13)	(0.09)		(1.61)	
Currency	0.00 %	0.11 %	0.02 %	0.31 %	0.41 %	-0.54 %	-0.59 %		-0.01 %	0.013
	(0.00)	(1.47)	(0.26)	(0.80)	(0.69)	(-2.31)	(-2.12)		(-0.85)	
Panel B: Seven factors and 6-Month Time Series Mom.										
Global	-0.04 %	0.00 %	-0.05 %	6.76 %	4.01 %	-0.17 %	-0.45 %	1.73 %	0.00 %	0.436
	(-0.64)	(0.01)	(-0.70)	(8.94)	(5.63)	(-0.64)	(-1.63)	(1.88)	(0.37)	
Macro	0.30 %	0.10 %	0.27 %	1.12 %	2.96 %	-0.13 %	-0.28 %	26.83 %	0.02 %	0.145
	(2.27)	(0.97)	(2.12)	(1.89)	(2.90)	(-0.28)	(-0.54)	(4.20)	(0.97)	
Currency	0.02 %	0.08 %	-0.01 %	0.48 %	0.52 %	-0.55 %	-0.64 %	8.01 %	-0.01 %	0.087
	(0.21)	(1.09)	(-0.17)	(1.20)	(0.88)	(-2.45)	(-2.50)	(3.77)	(-1.17)	

5.2 Seven Factor Model and Literature Factors

5.2.1 TSMOM factor

Rows (1)-(3) in table 5.2 shows the regression of the three hedge funds on the seven factors from Fung & Hsieh (2001). Rows (4)-(6) show the regression of the three hedge funds on the seven factors and the Time Series Momentum factor from MOP (2012). We see that the inclusion of the TSMOM increases adjusted R-squared for all the three hedge funds. While the Equity Market Factors are the best for explaining the Global Hedge Fund Index returns, the TSMOM factor is significant at the 95% level for all three hedge funds. Indicating that it helps explaining the returns obtained by these hedge funds.

The Equity Market factor and the Size Spread factor goes a long way in explaining the global hedge fund index with an adjusted R-squared of 0.402, which increases to 0.415 when including the TSMOM factor. The main contributor here is the Equity Market factor which here is represented by the SP500 Total Return Index. With the Global Hedge Fund Index including a wide variety of hedge funds, it seems only natural that a lot of them have exposure to this important index.

The TSMOM factor we include is also significant and can help explain some of the returns obtained by the Global Hedge Fund Index. One possibility here could be that it is a strategy used a lot in the Macro and Currency Hedge Funds, which is also included in the Global Index. This could make it significant even if most of the hedge funds do not employ these strategies.

For the Macro/CTA Index we see that a lot of the factors have significant t-stats, however, the adjusted R-Squared is rather low. By including the TSMOM factor it almost doubles from 0.063 to 0.118. In this respect the TSMOM factor seems to be very good at explaining the returns obtained by these hedge funds. We also see that the Equity factors are significant. In addition the PTFS Commodity factor is significant, although it only accounts for a small part of the returns obtained by these hedge funds.

As mentioned, the Macro Hedge Funds can trade virtually anything they want, and a lot of them trade commodities. As shown in HOP (2013), momentum strategies explain a lot of these funds' returns. Therefore it seems likely that some of the funds in this index use trend following strategies to achieve their return goals. They can also trade in currencies, which might be the reason why the TSMOM factor is significant and accounting for a lot of the returns obtained.

The Currency Hedge Funds does not have any alpha to explain, but from the table we can see that the PTFS for Currencies has a t-stat of 1.47 and the Bond factors are below -2. This could indicate that some of them are trading using these primitive currency strategies. Secondly, the bond factors might contribute

Table 5.2: **Seven Factor Model and TSMOM Factor**

Panel A shows the results from regressing the three hedge fund returns on the seven Fung & Hsieh factors. Panel B shows the regressions with the added TSMOM factor. Hedge fund returns are net of fees and the risk free rate. The t-stat is in brackets under the coefficient. The time period is from February 1998 to March 2019 for the Global and Macro Hedge Fund Indices, while the time period for the Currency Hedge Fund Index is from January 2005 to March 2019.

	PTFSBond	PTFSCurr.	PTFSComm.	EqMkt	SizeSpread	BondMkt	CreditSpread	TSMOM	Intercept (Alpha)	Adj. R-Sq
Panel A: Seven Factors										
Global	-0.034 %	-0.005 %	-0.024 %	7.366 %	2.888 %	-0.055 %	-0.327 %		0.013 %	0.402
	(-0.48)	(-0.09)	(-0.33)	(9.05)	(4.53)	(-0.18)	(-1.01)		(1.28)	
Macro	0.185 %	0.173 %	0.304 %	1.736 %	1.803 %	0.066 %	0.058 %		0.027 %	0.063
	(1.45)	(1.60)	(2.20)	(2.49)	(2.06)	(0.13)	(0.09)		(1.61)	
Currency	0.000 %	0.110 %	0.022 %	0.314 %	0.409 %	-0.540 %	-0.591 %		-0.010 %	0.013
	(0.00)	(1.47)	(0.26)	(0.80)	(0.69)	(-2.31)	(-2.12)		(-0.85)	
Panel B: Seven factors and Time Series Mom.										
Global	-0.032 %	-0.030 %	-0.038 %	7.499 %	3.034 %	-0.023 %	-0.308 %	0.652 %	0.009 %	0.415
	(-0.46)	(-0.50)	(-0.53)	(9.22)	(4.71)	(-0.08)	(-0.95)	(2.55)	(0.88)	
Macro	0.191 %	0.101 %	0.258 %	1.860 %	2.088 %	0.161 %	0.133 %	2.481 %	0.016 %	0.118
	(1.54)	(0.98)	(1.95)	(2.68)	(2.33)	(0.31)	(0.20)	(4.06)	(0.99)	
Currency	-0.017 %	0.075 %	-0.010 %	0.349 %	0.504 %	-0.517 %	-0.576 %	1.412 %	-0.015 %	0.099
	(-0.20)	(1.06)	(-0.13)	(0.92)	(0.86)	(-2.27)	(-2.13)	(4.07)	(-1.35)	

negatively because of interest rates. The TSMOM factor for currencies has a t-stat of 4.07 and a fairly high coefficient. In addition, the adjusted R-squared increases a lot from 0.013 to 0.099 with the inclusion of the TSMOM factor. This would indicate that time series momentum strategies for currencies is the best factor for explaining the currency trading hedge fund returns.

Overall the TSMOM factor seems like a good inclusion for explaining hedge fund returns with a linear factor model. In all three indices the addition of the TSMOM factor increases adjusted R-squared and reduces the alphas. The factor was also significant at a 0.02 level for the global index and at the 0.01 level for the Macro and Currency indices.

5.2.2 CSMOM factors

In table 5.3 we used the three cross-sectional momentum factors from AMP (2013). Row (1)-(3) shows the regression of the three hedge funds on the seven factors and the Low Cross Sectional Momentum factor. Row (4)-(6) shows the regression of the three hedge funds on the seven factors and the Middle Cross Sectional Momentum factor. Row (7)-(9) shows the regression of the three hedge funds on the seven factors and the High Cross Sectional Momentum factor. The low portfolio is not significant for any fund index, the middle portfolio is significant for the Global and Macro index, while the high portfolio is significant for all fund indices. The adjusted R-squared increases from low to middle to high for all portfolios with the exception of the currency index in CSMOM 2.

The low portfolio, CSMOM 1 is as mentioned not significant for any of the funds. It has t-stats of 0.859 for the Global index, -0.212 for the Macro index and -1.337 for the Currency index. The addition of this factor seems to have no improvement over the existing seven factor model.

The middle portfolio is improving the adjusted R-squared for the Global and Macro indices and is a significant factor for these two. However, the middle portfolio is not significant for the Currency index. Since that is the one index where the hedge funds primarily trade currencies one would expect that this one would be significant here, before the others. One explanation here might be that the factor is capturing other return patterns than just that of a cross sectional currency momentum strategy.

The high portfolio is highly significant for all three indices with t-stats of 4.073 for the Global index, 4.100 for the Macro index and 3.684 for the Currency index. It increases adjusted R-Squared of the Global index to 0.438 which is even higher than what was achieved by 7F+TSMOM. In addition it increases the adjusted R-Squared for the other two indices well above the other CSMOM factors.

The cross sectional momentum factors from AMP (2013) had mixed results. The low portfolio is a

Table 5.3: **Seven Factor Model and CSMOM Factors**

This table shows the cross-sectional momentum factor from AMP(2013) regressed on hedge fund returns in addition to the Fung & Hsieh factors. Panel A shows the results from the regression with the Low Cross Sectional Momentum factor. Panel B shows the results from the regression with the Middle Cross Sectional Momentum factor. Panel C shows the results from the regression with the High Cross Sectional Momentum factor.

	PTFSBond	PTFSCurr	PTFSCom	EqMkt	SizeSpread	BondMkt	CreditSpread	CSMOM	Intercept (Alpha)	Adj. R-Sq
Panel A: Seven factors and Cross Sectional Mom. 1										
Global	-0.04 %	-0.01 %	-0.02 %	6.82 %	2.85 %	-0.04 %	-0.30 %	0.46 %	0.01 %	0.402
	(-0.469)	(-0.155)	(-0.320)	(8.299)	(4.505)	(-0.106)	(-0.884)	(0.859)	(1.326)	
Macro	0.18 %	0.17 %	0.30 %	1.81 %	1.81 %	0.06 %	0.04 %	-0.15 %	0.02 %	0.059
	(1.439)	(1.613)	(2.190)	(2.420)	(2.065)	(0.109)	(0.060)	(-0.212)	(1.592)	
Currency	0.00 %	0.11 %	0.02 %	0.62 %	0.30 %	-0.56 %	-0.62 %	-0.52 %	-0.01 %	0.017
	(-0.029)	(1.480)	(0.307)	(1.289)	(0.520)	(-2.422)	(-2.274)	(-1.337)	(-0.979)	
Panel B: Seven factors and Cross Sectional Mom. 2										
Global	-0.04 %	-0.02 %	-0.04 %	5.51 %	2.65 %	0.06 %	-0.19 %	3.47 %	0.01 %	0.427
	(-0.464)	(-0.311)	(-0.442)	(7.608)	(4.383)	(0.209)	(-0.522)	(3.422)	(1.265)	
Macro	0.18 %	0.15 %	0.30 %	0.90 %	1.57 %	0.24 %	0.34 %	5.86 %	0.02 %	0.086
	(1.485)	(1.449)	(2.142)	(1.488)	(1.898)	(0.443)	(0.481)	(2.708)	(1.592)	
Currency	0.00 %	0.11 %	0.01 %	0.09 %	0.49 %	-0.52 %	-0.57 %	0.80 %	-0.01 %	0.013
	(-0.001)	(1.513)	(0.165)	(0.229)	(0.793)	(-2.215)	(-2.000)	(1.021)	(-0.749)	
Panel C: Seven factors and Cross Sectional Mom. 3										
Global	-0.01 %	-0.02 %	-0.06 %	5.38 %	2.73 %	0.11 %	-0.22 %	4.13 %	0.01 %	0.438
	(-0.210)	(-0.442)	(-0.763)	(7.681)	(4.536)	(0.369)	(-0.644)	(4.073)	(1.352)	
Macro	0.22 %	0.14 %	0.24 %	0.66 %	1.63 %	0.39 %	0.34 %	12.47 %	0.02 %	0.119
	(1.774)	(1.298)	(1.829)	(1.216)	(1.991)	(0.693)	(0.483)	(4.100)	(1.687)	
Currency	0.01 %	0.13 %	-0.02 %	-0.25 %	0.64 %	-0.49 %	-0.58 %	4.58 %	0.00 %	0.083
	(0.128)	(1.725)	(-0.285)	(-0.791)	(1.021)	(-2.086)	(-2.114)	(3.684)	(-0.366)	

very poor factor for explaining the hedge fund returns while the high portfolio seems like a good factor for explaining these returns. The middle portfolio places, maybe naturally, in the middle between these two.

5.3 Analysis and comparisons

From the regressions we see that the TSMOM factor and the 6MTSM factor both increase the adjusted R-squared for all three indices. While the TSMOM factor increases adjusted R-squared more for the Global and Macro index, the 6MTSM factor is the one that increases adjusted R-Squared the most for the Currency index. This indicates that the 6MTSM factor we developed is the one that is best suited to explain the currency hedge fund returns of the ones we haves tested.

Since we did not sort out only the alpha producing funds, but rather looked at representative indices there is not too large alphas to begin with. The small alphas of Global and Macro are further reduced by inclusion of several of the factors we looked at, which could mean that they do not have any alpha after controlling for these factors. It is important to note that this is net of all fees, which often are very large for hedge funds. A traditional fee structure is a 2% annual fee in addition to a 20% performance fee, with high-water marks or a hurdle rate. In this respect, it is quite impressive that the Global and Macro funds still managed to deliver rather strong results over this time period. The Currency index did not provide returns excess of the risk free rate in the period, but as previously mentioned, this period was seven years shorter and left out many years where the two other indices performed great.

To summarize, we can tell from the regressions that the inclusion of a broader currency momentum factor like the TSMOM and the middle and high CSMOM factors increases the explanation power of the seven factor model. In addition, several of the factors we include are highly significant for all the hedge fund indices.

Chapter 6

Conclusion

In this thesis we researched if a momentum strategy for currencies could help explain the returns of currency trading hedge funds. We included a Global Hedge Fund Index and a Macro Hedge Fund Index in addition to the Currency Hedge Fund Index to better compare the inclusion of a currency momentum strategy. Several of the factors we use in our regressions seems to improve the seven factor model normally used to explain hedge fund returns.

We did not manage to find the same results as MOP (2012), regarding the trend identification and reversals. The sample period differences made the comparisons between the MOP (2012) factor and the 6MTSM factor difficult. What we did find was visual indications of trends and momentum before the global financial crisis looking at the cumulative returns from the constructed momentum strategies. Both the Global Index and the Macro Index showed similar patterns before the financial crisis. An increasing cumulative return. Post crisis, all the indices and the 6MTSM factor also shows similar patterns, but now the cumulative returns are stable and not increasing.

With regards to our research question, our results indicate that both a cross sectional momentum strategy and a time series momentum strategy can on their own increase the explanation power of the linear regression model developed by Fung & Hsieh (2001). This is interesting seeing as they already included a currency factor, although this factor is a very simple representation of a trend following strategy.

Our findings are in line with the research from Baltas & Kosowski (2012) and HOP (2013) which both find that momentum strategies does well in explaining returns of CTAs and Managed Futures funds. Although not directly comparable, the fact that our results are similar to those of the other papers indicate that the extended seven factor model gives reasonable results.

Possible extensions of this work is to experiment with other factors and currency pairs to further increase the explanatory value of the factor. It could for example be interesting to see a factor with more than just the 8-9 most traded currency pairs. Problems with high transaction costs could be bigger for this kind of strategy and that might be one of the reasons this has not been researched extensively yet.

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Appendix

Table 6.1: **Summary statistics on excess returns**

Currency	Annualized Mean	Annualized volatility
EUR/USD	0.31%	10%
GBP/USD	0.33%	8.60%
JPY/USD	-2.53%	9.64%
CHF/USD	-4.77%	10.24%
AUD/USD	-3.60%	12.52%
NZD/USD	-4.47%	13.04%
CAD/USD	-0.92%	9%

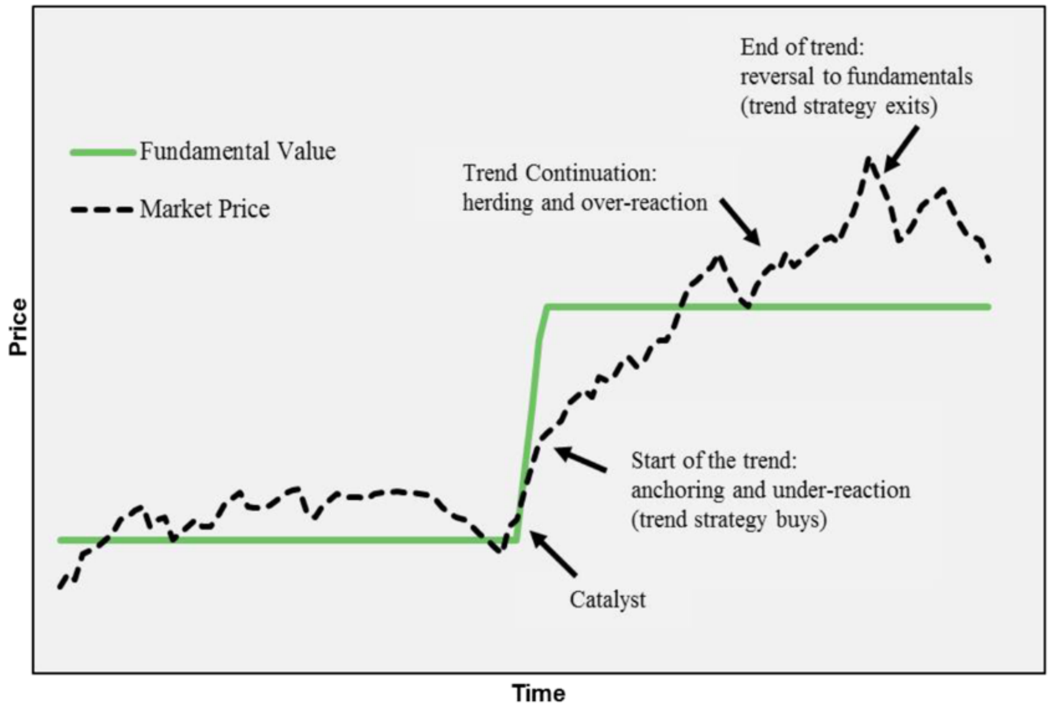

Figure 6.1: **Life cycle of a trend - Demystifying Managed Futures (2013)**

The figure shows a case where new information has hit the market and changed the fundamental value. The theory then says that because of the effects of anchoring and the disposition effect the market price is not fully reflecting the new "correct" value. Over time the market price moves towards the fundamental value, and this price move is extended beyond the fundamental value because of effects like herding, confirmation bias and fund flows.

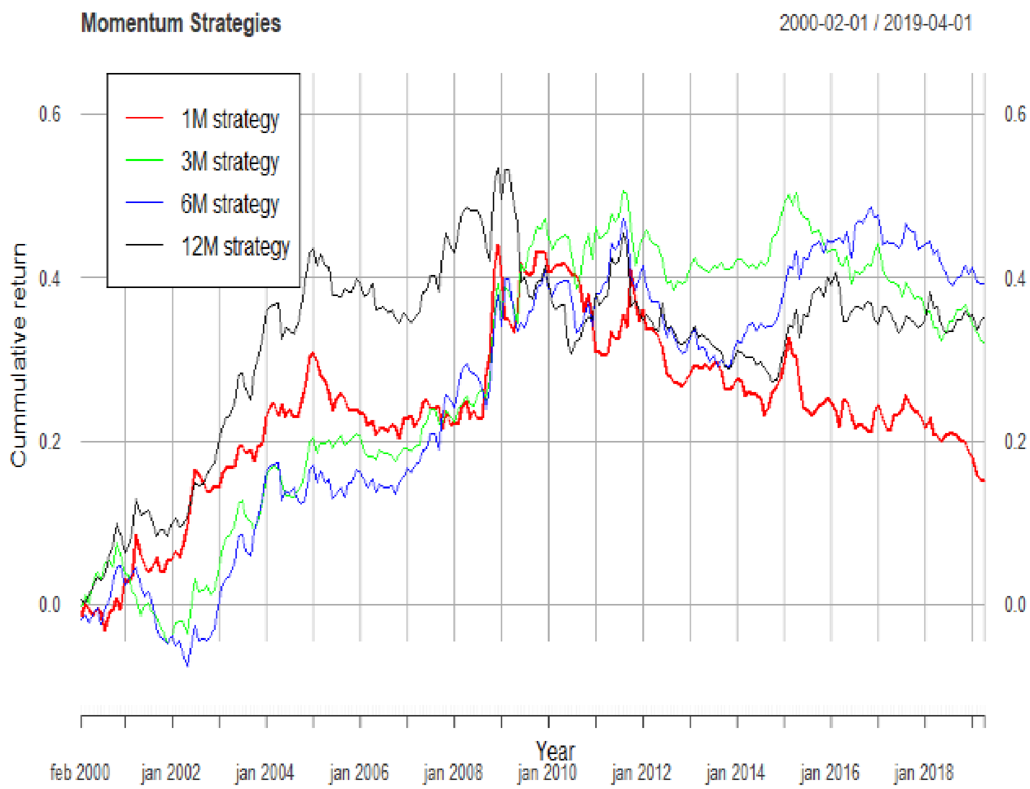

Figure 6.2: **Momentum strategies for our own factor**

The figure shows Cumulative returns of 1-month, 3-month, 6-month and 12-month look-back periods, and 1-month holding period.

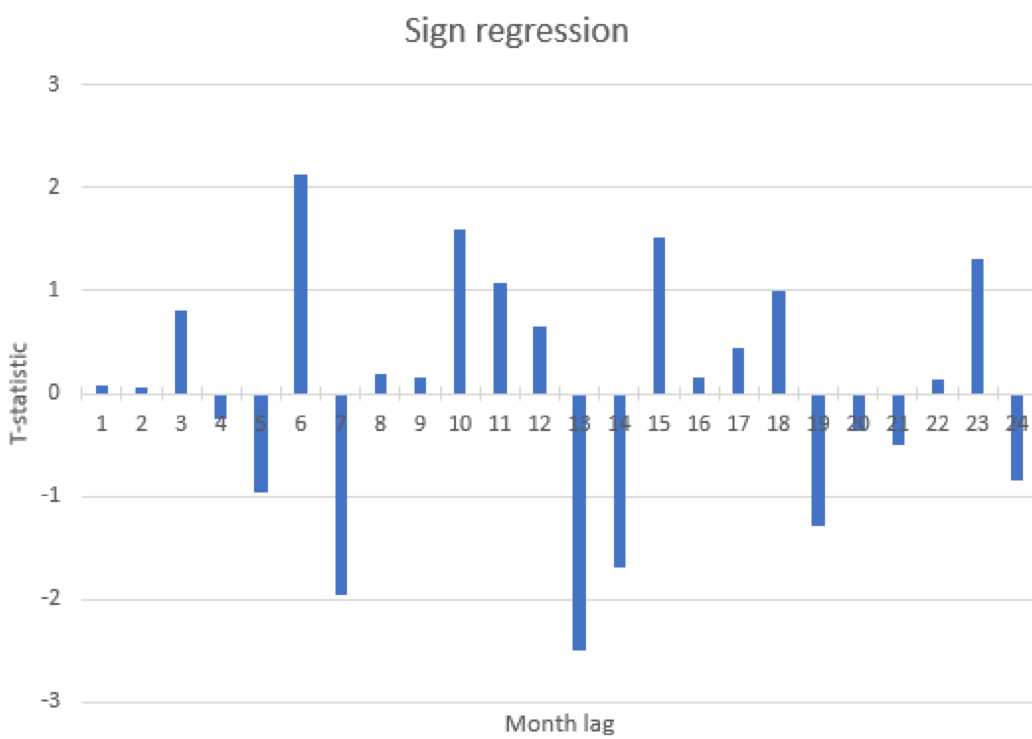

Figure 6.3: **T-Values for sign regression**

This figure shows the t-statistic from a panel regression ran on the sign-regression:

$r_t^k = \alpha + \beta_h sign(r_{t-h}^k) + \epsilon_t^k$