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Commodity Markets: An Updated Study of the "Timed Momentum" Trading Strategy

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Abstract

This thesis provides the reader with an updated study of the "timed momentum" strategy proposed by Miffre and Basu (2008). Their article shows that this commodity trading strategy is able to achieve significant mean returns, Sharpe ratios and alpha values. However, their sample period is from 1994 to the end of 2007. This is a time-period where a broad range of commodities in general experienced a significant price growth, and some may argue that the success of this trading strategy is simply due to this.

The main objective of this thesis is to see if the "timed momentum" trading strategy is still profitable, given newer and additional data. Hence, this thesis extends the sample period to capture both a bear and a bull market for commodities, and is inspired by the general need for research to support or reject previous findings.

My results shows that the "timed momentum" strategy is on average still profitable, but that the average risk associated with it has risen. The average annual return generated varies from -3.4% to 22.6%, with an average annual volatility of around 31%. Further, I find that the "timed momentum" strategy appears to not be as profitable as Miffre and Basu (2008) argue it is. However, my results shows that significant profits could have been made using this strategy in the period from 1998 to the end of 2015, which should be interesting for commodity fund managers. My results also demonstrates that this strategy appears to have superiority over long-only trading strategies.

Abstrakt

Denne masteroppgaven er en oppdatert studie av «timed momentum» tradingstrategien foreslått og utviklet av Miffre og Basu (2008). Deres artikkel viser at denne råvaretradingstrategien har evnen til å generere signifikante gjennomsnittsavkastninger, Sharpe-ratioer og alpha verdier. Når det er sagt så legger de tidsperioden fra 1994 til slutten av 2007 til grunn for deres analyser. Dette er en tidsperiode preget av en generell sterk prisvekst på råvarer, og mange kan derfor hevde at suksessen til denne strategien skyldes denne prisveksten isolert og ikke strategien selv.

Hovedmålet til denne masteroppgaven er å undersøke om «timed momentum» tradingstrategien fremdeles er lønnsom, gitt at man tar hensyn til nyere og flere data i analysene, slik at tidsperioden opplever både ett bear og ett bull marked. Denne masteroppgaven er derfor motivert av det generelle behovet for forskning som kan bekrefte eller avkrefte tidligere funn.

Mine resultater viser at «timed momentum» strategien fremdeles i snitt er lønnsom, men at risikoen assosiert med den har steget. Årlig gjennomsnittlig avkastning generert varierer fra -3.4% til 22.6%, med en gjennomsnittlig årlig volatilitet på rundt 31%. Videre finner jeg at strategien ikke virker like lønnsom som det Miffre og Basu (2008) hevder den er. Til tross for dette viser resultatene mine at man kunne oppnådd stor profitt ved å bruke denne strategien i tidsperioden fra 1998 til slutten av 2015, noe som bør være interessant for råvarefond forvaltere. Mine resultater viser også at denne strategien ser ut til å ha overtaket på long-only tradingstrategier.

I – Introduction

The growth in commodity futures investments has been considerable over the last decades, where the net notional value of trading more than doubled from roughly $170 bn to $410 bn from 2007 to 2013 (Bessler & Wolff 2015). In as recently as 1999, the total amount invested in investment vehicles tracking the Standard and Poor's GSCI index, the first major investable commodity index and a widely recognized benchmark, were estimated to be less than $5 bn (Büyükşahin et al. 2008). Hence, there is no doubt that commodities as an asset class has grown significantly and established itself as an attractive alternative to more traditional asset classes among institutional asset managers and private investors. Unsurprisingly, this has led to the publication of numerous research articles regarding alpha generation in commodity markets.

One of these articles, by Miffre and Basu (2008), examine a simple timing strategy for commodity momentum based on whether the market is in backwardation or contango. They argue that the Commitment of Trader's report, published by the CFTC[1], suggest that markets regularly move between backwardation and contango, and because of this is it natural to examine whether one can time long-short momentum strategies based on these phases. To do this, they consider the return of a commodity index as a simple proxy and timing signal for backwardation or contango. Their "timed momentum" strategy goes long previous winner commodities if the return on the index in the past was positive, and shorts the loser commodities if it was negative. The objective is hence to buy backwardated contracts and sell contangoed ones. Their analysis provides evidence that commodity momentum is a dynamic phenomenon, and that the strategy presented in their article is able to achieve mean returns ranging from 25% to 30%, Sharpe ratios ranging from 1.96 to 2.38, and significant alpha values.

Their sample period is from 1994 to the end of 2007. This is a time-period where a broad range of commodities in general experienced a significant price growth. It is therefore reasonable to ask; given additional and newer data, is the "timed momentum" strategy proposed by Miffre and Basu (2008) still profitable? The objective of this thesis is to answer that question, by extending the sample period to capture both a bear and a bull market for commodities. Empirical findings are more robust with longer time-periods and more data. Hence, this thesis is motivated by the general need for research to support or reject previous findings. Further, any results I find should be of interest for commodity fund managers.

[1] The U.S. Commodity Futures Trading Commission

If the trading strategy worked in the past, it may also generate abnormal returns to their clients in the future. If it did not work in the past, should they probably stay away from this kind of trading strategy in the future as well. Hence, regardless of the overall conclusion, the information is of value.

My results shows that the "timed momentum" strategy is indeed still profitable even after extending the sample period to the end of 2015. More specific, using 12-week and 24-week formation periods[2] generates average annual returns of 23% and 17% respectively. The average annual volatility is around 31% across all formation periods considered. However, the annual returns generated in general is lower now than when Miffre and Basu (2008) did their study. In addition, the average annual volatility has risen. Still, my results confirms the superiority of long/short trading strategies over long-only strategies.

The rest of this thesis is structured as follows. Section II introduces the reader to previous research on the topic of momentum strategies. Section III provides the reader with the details of the data set. Section IV demonstrate the method applied. Section V presents the results. Section VI concludes.

[2] When considering for example a four week formation period, I calculate the past four-week period return in each commodity and the index, and use these returns in choosing which commodities that will be part of the "timed momentum" portfolio. Hence, the formation period is the length of how far back I look when calculating the returns. For instance, when implementing a 12-week formation period, I calculate the previous 12-week returns.

II – Literature Review

As mentioned in the introduction, the growth in commodity market investments has been substantial in recent decades – but why is that?

One of the easiest ways to get a better understanding of this growth is to compare the benefits of commodity trading with trading in other assets. First, the nearby commodity futures contracts are in general very liquid (Chong & Miffre 2006) and cheap to trade. For instance, Shen et al. (2007) estimated transaction costs for five CME commodity contracts based on the renowned study by Locke and Venkatesh (1997). These transaction cost estimations varies from a low of 0.044% of notional contract value for Live Cattle futures to a high of 0.146% for Pork Bellies. In comparison, the transaction costs for large institutional investors range from 0.58% when buying S&P500 stocks (Fleming et al. 1996) to more than 4% for trades in small-cap stocks (Bhardwaj & Brooks 1992; Stoll & Whaley 1983). Second, commodity futures are not subject to short-selling restrictions (Miffre & Rallis 2007). Hence, the ability to take a short position, which is a key element of most active trading strategies, is as easy as taking a long position and the transaction costs associated with the two types of positions are identical. Third, diversification benefits. Commodities are often seen as a natural hedge against unexpected inflation[3], as it has an opposite exposure to inflation compared to stocks and bonds (Gorton & Rouwenhorst 2004; Erb & Harvey 2006). Unlike stocks, commodity futures prices are not driven by analyst recommendations or corporate earnings announcements, but are rather related to other risk factors such as weather, geopolitical events, and supply conditions (Daskalaki et al. 2014). The article by Erb and Harvey (2006) supports this, as it gives empirical evidence that commodity futures have low return correlations with traditional assets, which implies that commodities are valuable tools for strategic asset allocation. This view is supported by Gorton and Rouwenhorst (2004), which states that much of the attraction of commodities appears to be due to the fact that they produce equity-like returns, while having low or even negative correlation with both equities and bonds.

Given the many benefits of commodities as an asset class, several articles has been published on the topic of alpha generation and more specifically, momentum trading. The momentum literature focuses on the relative outperformance of securities in a cross-section, while time series momentum focuses purely on a securities own past. Common to both definitions is that past performance is considered a useful guide to future returns.

[3] In order to calculate unexpected inflation, Gorton & Rouwenhorst (2004) uses the short-term T-bill rate as a proxy for the market's expectation of inflation. Consequently, unexpected inflation is measured as the actual inflation rate minus the nominal interest rate (which is known ex ante). See Gorton & Rouwenhorst (2004) for more details and further discussions.

Asness et al. (2013) examined eight different markets and asset classes and focused on the interaction between cross-sectional momentum strategies and their common factors. Those markets and asset classes included individual stocks in the U.S, the U.K, Europe, and Japan; equity index futures; government bonds; currencies; and commodity futures. They found consistent and universal evidence of momentum return premia across all the markets they studied. Further, they found striking momentum correlation patterns across asset classes, which they suggest are related to common global momentum factors.

Shen et al. (2007) conducted a comprehensive research of momentum strategies in commodity futures markets, and found that momentum strategies generate significant positive returns for short and intermediate time horizons. More specific, they found that 24 out of 28 commodities in their sample gave a positive contribution to their 2-month formation period strategy. Further, they argue that it is extremely unlikely that the momentum profits generated could be eliminated by transaction costs, if the strategy was applied in a real-world scenario. They estimate an excess return of 0.4% - 0.8% per month after transaction costs.

The article by Miffre and Rallis (2007) studies the profitability of 56 momentum and contrarian strategies in commodity futures markets. The momentum strategies buys the commodities that had a positive return in the recent past, sells the commodities that had a negative return, and holds these portfolios for up to 12 months. The contrarian strategies does the opposite. The article finds that the contrarian strategies don't work, but that 13 of the momentum strategies are profitable, which generated an average return of over nine percent a year. This strategy is quite similar to the "timed momentum" strategy, but it does not incorporate a commodity index as an additional trading signal.

Fuertes et al. (2015) goes one step further. They suggest a trading strategy that incorporates three different signals; momentum, term structure, and idiosyncratic volatility. The strategy buys commodity futures with high past performance, high roll-yields, and low idiosyncratic volatility. Further, the strategy shorts commodity futures with poor past performance, low roll-yields, and high idiosyncratic volatility.
They demonstrates that these signals are non-overlapping when applied to commodities, and that this trading strategy generates a significant Sharpe ratio which is robust to transaction costs and that is higher than if you only use the signals in isolation or in pairs. In addition, they also demonstrate that using the momentum signal individually does indeed generate excess returns and significant Sharpe ratios as well.

Hence, several articles shows that positive returns can be generated using momentum strategies, which is a significant aspect to the ongoing market efficiency debate. Chevallier et al. (2013) tries to give the reader a better understanding of momentum and trends in commodity markets and other asset classes. One of the problems with momentum strategies is that changes are difficult to forecast. Business cycles, political events and/or technical innovations can affect trends significantly, which lowers the probability of having stable trends over time. The article decomposes trends into a combination of expected returns and corresponding volatility, and estimates Markov-Switching models for individual time series. Their results shows that commodities in general and energy commodities in particular, has stronger trends than other asset classes like equities and currencies. This should make a strong case for using commodities in particular in momentum strategies. However, they also point out that there are differences across commodities in how persistent trends may be.

Moskowitz et al. (2012) argue that time series momentum meet the expectations of many prominent behavioral pricing theories. Their findings of positive time series momentum that reverse partially over time may be consistent with initial under-reaction and delayed over-reaction. They argue that their findings of consistent time series momentum across nearly five dozen futures contracts and several major asset classes over the last 25 years challenge the "random walk" hypothesis which states that past price history are not useful when forecasting which direction the price will take in the future. Further, they finds that both spot price changes driven by information shocks and roll yields stemming from the shape of the futures curve contributes to time series momentum. In addition, they argue that speculators profit from time series momentum at the expense of hedgers. This is consistent with speculators receiving a premium for giving liquidity to hedgers.

The "timed momentum" strategy aims to buy backwardated contracts and sell contangoed ones, which is in the line of reasoning with the hedging pressure hypothesis (Erb & Harvey 2006). This hypothesis is an attempt to describe the absence of consistent empirical support for the theory of normal backwardation, formulated by Keynes (1930) and Hicks (1939).

The theory of normal backwardation argue that the commodity futures price should be less than the expected future spot price to facilitate hedging opportunities for producers who sell their output forward. Hence, hedgers must offer speculators in commodity futures an insurance premium. In other words, excess returns should in general be positive so net long speculators earn a premium for taking on the risk that net short hedgers are willing to get rid of. The theory for normal backwardation thus provides a rational for long-only commodity futures investments as it is expected that the futures prices rises as maturity approaches. Normal backwardation is impossible to observe however, since the expected future spot price is impossible to know, but a good indicator would be if excess returns for individual commodity futures were observed over a historical period. However, empirical support in favor of the normal backwardation theory is in general weak. Kolb (1992) studies the price behavior of 23 commodity futures and claims that "normal backwardation is not normal".

In addition, research shows that long-short commodity portfolios perform better than long-only commodity portfolios on a risk-adjusted basis (Miffre 2011), which is further evidence against the theory of normal backwardation.

The hedging pressure hypothesis, proposed by Cootner (1960), allows for the possibility of net long, as well as net short, hedgers. The normal backwardation theory argues that the futures price has to be set lower than the expected spot price at maturity when hedgers are net short, to induce speculators to take long positions. In addition, the hedging pressure hypothesis notes that the futures price has to be set higher than the expected spot price at maturity when hedgers are net long, to induce speculators to take short positions. Hence, if the hedging pressure hypothesis holds, speculators should get a reward for taking long positions in backwardated contracts (when hedgers are net short) and for taking short positions in contangoed contracts (when hedgers are net long). The reason for this is that, according to the hedging pressure hypothesis, the futures price of a backwardated/contangoed contract is expected to increase/decrease in the direction of the expected spot price as maturity approaches. The empirical support is stronger for this hypothesis than the normal backwardation theory, which also gives strong motives for dynamic trading strategies (Miffre 2015).

Miffre (2015) points out that the reasons behind momentum profits are still highly debatable. For example, support of both behavioral explanations and rational pricing explanations has been brought forward. On one hand, it is shown that momentum profits in long-short portfolios eventual reverse on the long term. Many consider this as a sign of initial under-reaction and subsequent mean-reversion. On the other hand, several articles argue that the reason to why momentum strategies works well is that it selects the commodities that are likely to perform well in line with the theories of storage and the hedging pressure hypothesis.

To summarize, there are several benefits with commodity futures that makes them attractive to use in a long/short trading strategy compared to a long-only strategy. In particular, low transaction costs, no short-selling restrictions, and high liquidity contributes to this. Several studies shows that momentum strategies has indeed generated abnormal returns in commodity markets, even after incorporating transaction costs. But, most of these studies has been conducted before the financial crisis. However, it has been revealed that trends has been particular strong in commodity markets compared to other asset classes. This provides us with a strong incentive to update the study of the “timed momentum” strategy, to see if this strategy is still profitable when newer market data are considered. The reasons behind momentum profits, and what it is that causes them, are controversial however, and still up for debate.

III – Data

My data collection, obtained from Quandl's Stevens Continuous Futures database, contains settlement prices on 23 US commodity futures contracts. There are 12 agricultural futures (cocoa, coffee, corn, cotton, oats, orange juice, soybean meal, soybean oil, soybeans, sugar, rough rice, wheat), 2 livestock futures (lean hogs, live cattle), 5 metal futures (copper, gold 100 oz, palladium, platinum, silver 5000 oz), 3 oil and gas futures (heating oil, WTI crude oil, natural gas) and the futures on lumber. The choice of commodities is influenced by the desire to have a wide cross section, as Miffre and Basu (2008) argue that momentum effects are stronger across a broad cross section. The sample period is from 1994 to the end of 2015 and captures both a bear and a bull market for commodities.

Miffre and Basu (2008) consider 33 commodities with a sample period from 1994 to the end of 2007. My thesis consider a smaller number of commodities due to lack of data availability. The commodities considered by Miffre and Basu (2008), which is not considered in this thesis is; milk, aluminum, coal, white wheat, feeder cattle, frozen pork bellies, regular and unleaded gas, diammonium phosphate, ethanol and western plywood. However, we add rough rice to our sample. Because of this, the underpinning of my results will be somewhat different from Miffre and Basu (2008).

The continuous futures datasets have no price adjustments, which means that the data used in my calculations reflects actual transaction prices. Further, to secure liquidity for potential investors, I apply a liquidity-based roll method to the datasets. This means that the roll date on the futures contracts is on the first day that the back contract has a higher open interest than the front contract. I consider this approach as more realistic and hands-on for real-life commodity trading. Not to mention, the aim of the strategy is to buy backwardated contracts and sell contangoed contracts. Hence, part of the momentum profit will come from the profits generated on the roll-over trades, so adjusting the price levels on the roll-over date might eliminate parts of the momentum profits that the strategy is trying to earn (Miffre & Rallis 2007).

I use weekly Wednesday prices to ensure that my results are not influenced by any weekend effects. This gives me 1137 observations over the total sample period. In the rare case that Wednesday was a holiday, the settlement price at the next trading day was used instead. I consider commodities as any other financial asset and choose to work with the logarithm of returns of these settlement prices, since returns by construction is trend-stationary.

Table one below gives descriptive statistics on each commodity in the sample, the Rogers International Commodity Index (RICI), and the S&P500 over the total time-period from 1994 to the end of 2015.
The first thing to notice is that the chosen commodities on average has delivered lower annual returns than both the RICI and the S&P500, with over ten percentage points higher annual volatility. Also, notice that S&P500 has performed better than the RICI, with lower volatility. Interestingly, the chosen commodities on average has the least negative skewness, which implies that they has a less negative skewed return distribution than the RICI and the S&P500. Another interesting feature is that the S&P500 observe more extreme returns, that is, has the highest excess kurtosis, but still has the lowest annual volatility on average. Looking at the commodities individually we see that the five best performing commodities for this period is cocoa, copper, gold, palladium, and silver. All of these delivered an average annual return that were higher than the RICI, but none of them was able to beat the S&P500 on average. Of these five commodities, only gold delivered a lower average annual volatility than the RICI, which was equal to the average volatility of the S&P500. The five worst performing commodities for this period were cotton, soybean oil, rough rice, natural gas, and lumber. Both cotton and lumber delivered negative average annual returns, and natural gas had an average annual volatility of over fifty percent in this time-period. The excess kurtosis were highest among coffee, live cattle, and lean hogs. Coffee and lean hogs were also among those commodities that generated the most positive return distribution, along natural gas and wheat.

Maybe even more interesting is it to compare table two and table three below, as there is some significant differences in the futures data from the period Miffre and Basu (2008) did their research, to the period that followed up until the end of 2015.

In the sample period from 1994 to the end of 2007, there are only two commodities that delivers a negative annual return on average; cotton and lumber. The five best performing commodities in this period was copper, platinum, heating oil, WTI crude oil, and natural gas. The average annual return across all commodities in the sample is almost five percent. Further, the RICI has an average annual return of 16.5%, which is twice as high as the S&P500; with approximate the same level of risk. The excess kurtosis is now higher for the individual commodities on average, than the S&P500.

The sample period from 2008 to the end of 2015 looks quite different. Now, eighteen of the commodities in the sample delivers a negative annual return on average. Only cocoa, sugar, live cattle, gold, and palladium delivered a positive annual return on average in this time-period. The average annual return across all commodities in this time-period is -2.7%. In addition, the RICI has an average annual return of -9.9 %.
For comparison, the S&P 500 delivered 3.9 %. Further, the excess kurtosis was much higher for the S&P500 in this time-period than both the average of the individual commodities and the RICI.

To summarize, most of the commodities in the sample experienced a price growth until the financial crisis. Since then, the general price development has been more volatile with smaller trends. However, notice that the annual volatility on average for all individual commodities remains roughly stable across time.

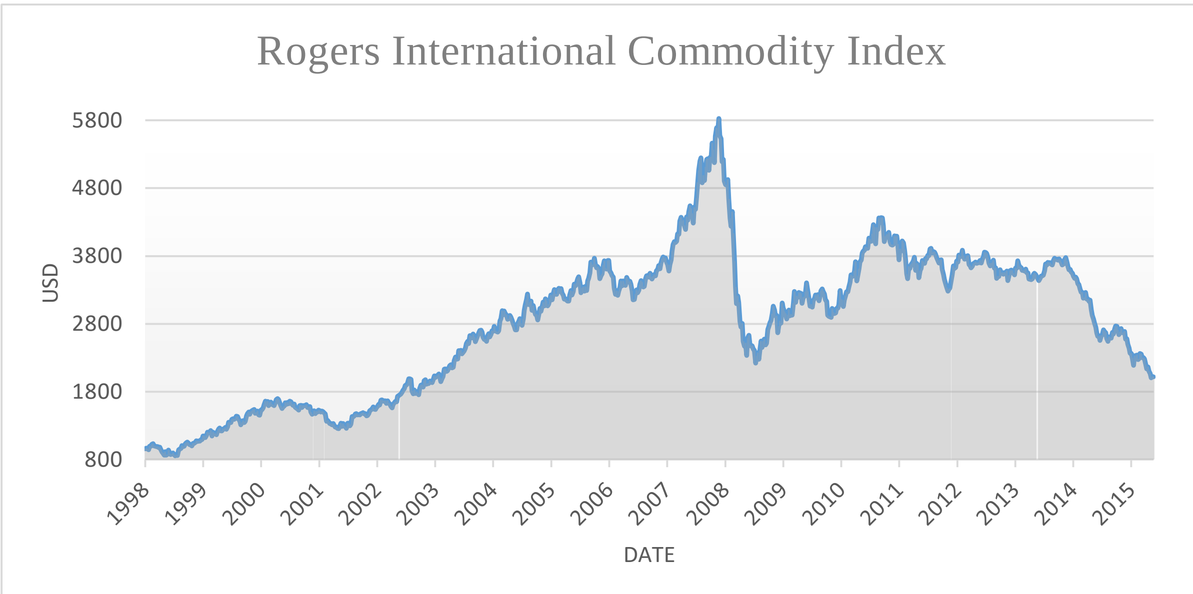


Table 1: Descriptive Statistics Weekly Data (Total Sample Period)

	Annual Returns	Annual Volatility	Excess Kurtosis	Skewness	Maximum	Minimum
Cocoa	4.8 %	28.3 %	1.30	0.17	20.2 %	-14.1 %
Coffee	2.5 %	39.0 %	5.17	0.48	38.0 %	-28.0 %
Corn	0.7 %	28.6 %	4.09	-0.24	15.3 %	-29.0 %
Cotton	-0.3 %	25.7 %	4.63	-0.51	15.0 %	-25.6 %
Oats	2.2 %	32.9 %	2.85	0.06	28.0 %	-20.7 %
Orange Juice	1.1 %	31.9 %	1.86	0.12	19.0 %	-22.0 %
Soybean Meal	1.3 %	27.9 %	2.69	-0.32	16.1 %	-23.1 %
Soybean Oil	0.3 %	23.3 %	1.16	-0.07	13.3 %	-12.5 %
Soybeans	1.0 %	25.1 %	2.96	-0.54	14.2 %	-20.6 %
Sugar	1.6 %	32.9 %	1.62	-0.04	20.1 %	-21.5 %
Rough Rice	0.03 %	26.8 %	3.26	0.05	27.1 %	-16.7 %
Wheat	0.9 %	29.7 %	1.60	0.44	20.5 %	-17.7 %
Live Cattle	2.9 %	16.8 %	5.31	-0.50	8.8 %	-19.3 %
Lean Hogs	1.2 %	32.6 %	5.13	0.52	29.5 %	-19.4 %
Copper	4.5 %	26.1 %	2.27	-0.32	15.0 %	-18.5 %
Gold	4.5 %	17.0 %	4.37	-0.31	12.9 %	-13.2 %
Palladium	6.7 %	33.5 %	2.38	-0.35	19.3 %	-23.3 %
Platinum	3.6 %	22.7 %	3.23	-0.45	12.8 %	-16.6 %
Silver	4.6 %	29.9 %	4.18	-0.63	14.8 %	-29.5 %
Heating Oil	3.8 %	31.3 %	1.16	0.01	16.6 %	-20.4 %
WTI Crude Oil	4.0 %	32.3 %	2.51	-0.31	23.2 %	-25.3 %
Natural Gas	0.3 %	52.3 %	2.81	0.47	51.1 %	-25.7%
Lumber	-2.5 %	32.3 %	0.67	0.35	20.4 %	-14.0 %
Average[4]	2.2 %	29.5 %	2.92	-0.08	20.5 %	-20.7 %
RICI[5]	4.3 %	18.9 %	1.71	-0.27	10.5 %	-10.9 %
S&P500	6.8 %	17.0 %	5.06	-0.79	10.3 %	-17.5 %

[4] Average of the commodity futures data listed above in the table.

[5] Rogers International Commodity Index. Available sample period is from 12.08.1998 to the end of 2015. Hence, the calculations in this row is based on only 900 weekly observations. The data was collected from Quandl. More about this index and its uses in the Method section.

Table 2: Descriptive Statistics Weekly Data (1994 – 2007)[6]

	Annual Returns	Annual Volatility	Excess Kurtosis	Skewness	Maximum	Minimum
Cocoa	4.2 %	28.5 %	1.75	0.26	20.2 %	-14.1 %
Coffee	4.5 %	41.9 %	5.58	0.51	38.0 %	-28.0 %
Corn	2.8 %	25.9 %	6.95	-0.33	13.8 %	-29.0 %
Cotton	-0.1 %	22.8 %	6.95	-0.41	15.0 %	-25.6 %
Oats	6.0 %	30.5 %	2.43	-0.04	19.4 %	-20.7 %
Orange Juice	1.9 %	28.6 %	1.70	0.11	18.7 %	-14.9 %
Soybean Meal	3.9 %	26.3 %	3.93	-0.50	11.6 %	-23.1 %
Soybean Oil	3.8 %	21.7 %	1.26	0.12	13.3 %	-11.5 %
Soybeans	4.1 %	23.5 %	4.25	-0.54	14.2 %	-20.6 %
Sugar	0.1 %	30.5 %	1.46	-0.14	16.7 %	-14.7 %
Rough Rice	1.2 %	27.4 %	4.34	0.21	27.1 %	-16.7 %
Wheat	6.4 %	26.4 %	0.89	0.46	15.2 %	-10.6 %
Live Cattle	1.9 %	17.0 %	7.36	-0.82	8.7 %	-19.3 %
Lean Hogs	2.0 %	34.2 %	5.22	0.46	29.5 %	-19.4 %
Copper	9.9 %	24.6 %	2.47	-0.25	15.0 %	-18.5 %
Gold	5.4 %	14.5 %	4.74	0.26	12.9 %	-11.0 %
Palladium	7.7 %	32.5 %	2.95	-0.11	19.3 %	-20.3 %
Platinum	9.8 %	19.7 %	3.27	-0.22	12.8 %	-13.9 %
Silver	7.7 %	25.6 %	3.62	-0.38	14.8 %	-20.0 %
Heating Oil	12.3 %	31.2 %	0.70	-0.01	15.6 %	-20.4 %
WTI Crude Oil	13.2 %	30.5 %	2.06	-0.51	13.1 %	-25.3 %
Natural Gas	8.9 %	53.9 %	0.89	0.23	31.7 %	-25.7 %
Lumber	-3.9 %	30.9 %	0.20	0.26	18.2 %	-12.7 %
Average	4.9 %	28.2 %	3.26	-0.06	18.0 %	-19.0 %
RICI	16.5 %	16.8 %	0.78	0.01	9.2 %	-9.0 %
S&P500	8.4 %	15.9 %	2.44	-0.32	10.3 %	-10.9 %

[6] The number of observations behind these calculations are 722, except for the RICI row where the calculations are based on 485 observations.

Table 3: Descriptive Statistics Weekly Data (2008 – 2015)[7]

	Annual Returns	Annual Volatility	Excess Kurtosis	Skewness	Maximum	Minimum
Cocoa	5.8 %	27.9 %	0.46	-0.01	12.4 %	-10.4 %
Coffee	-1.0 %	33.4 %	1.75	0.34	20.1 %	-14.7 %
Corn	-2.9 %	32.7 %	1.55	-0.14	15.3 %	-16.3 %
Cotton	-0.7 %	30.3 %	2.46	-0.56	13.3 %	-22.3 %
Oats	-4.4 %	36.6 %	2.91	0.19	28.0 %	-18.3 %
Orange Juice	-0.2 %	37.1 %	1.47	0.14	19.0 %	-22.0 %
Soybean Meal	-3.2 %	30.4 %	1.30	-0.11	16.1 %	-15.0 %
Soybean Oil	-5.9 %	25.9 %	0.82	-0.23	12.4 %	-12.5 %
Soybeans	-4.4 %	27.7 %	1.52	-0.49	13.2 %	-14.4 %
Sugar	4.1 %	36.7 %	1.51	0.04	20.1 %	-21.5 %
Rough Rice	-2.0 %	25.7 %	0.79	-0.30	10.7 %	-13.1 %
Wheat	-8.7 %	34.7 %	1.56	0.46	20.5 %	-17.7 %
Live Cattle	4.6 %	16.5 %	1.29	0.11	8.8 %	-7.4 %
Lean Hogs	-0.04 %	29.6 %	4.38	0.65	21.1 %	-15.4 %
Copper	-4.9 %	28.3 %	1.88	-0.35	12.7 %	17.0 %
Gold	3.1 %	20.6 %	3.03	-0.62	10.9 %	-13.2 %
Palladium	5.0 %	35.2 %	1.61	-0.69	12.6 %	-23.3 %
Platinum	-7.1 %	27.2 %	2.29	-0.50	12.5 %	-16.6 %
Silver	-0.9 %	36.1 %	3.31	-0.71	14.1 %	-29.5 %
Heating Oil	-10.8 %	31.5 %	1.99	0.03	16.6 %	-18.2 %
WTI Crude Oil	-12.1 %	35.2 %	2.88	-0.03	23.2 %	-23.3 %
Natural Gas	-14.8 %	49.4 %	7.65	1.00	51.1 %	-19.3 %
Lumber	-0.1 %	34.7 %	1.09	0.45	20.4 %	-14.0 %
Average	-2.7 %	31.5 %	2.15	-0.06	17.6 %	-17.2 %
RICI	-9.9 %	21.0 %	1.76	-0.33	10.5 %	-10.9 %
S&P500	3.9 %	18.6 %	7.11	-1.27	9.4 %	-17.5 %

[7] The number of observations behind these calculations are 415.

IV – Methodology

The objective of Miffre and Basu (2008) is to capture phases of backwardation and contango using a simple trading strategy they call "timed momentum" strategy. A key part of this strategy is to use the return on a commodity index as a simple proxy for backwardation or contango, and hence as a timing signal. It is not clear which index they use, as they mention both the Rogers International Commodity Index (RICI) and the Thomas Reuters CRB index in their article. However, due to data availability I choose to work with RICI.

RICI is a composite, USD based, total return index designed in the late 1990s. This index represents the value of a basket of commodities consumed in the global economy, ranging from agricultural to energy to metal products, and aims to be a global measure of the price action of raw materials. Hence, the index's commodity weights intentions is to reflect consumption patterns worldwide (The RICI handbook 2016)

The main motivation behind the choice of index in Miffre and Basu (2008) was that the index had to be constituted by a fixed set of liquid commodities. At that time, their index was built on 17 different commodities. Today, 37 different commodity futures contracts constitutes the RICI. Since the index now considers 20 commodities more than when Miffre and Basu (2008) did their study, my results are not directly comparable to their results. I could try to construct a similar index, based on the same 17 commodities as when Miffre and Basu (2008) conducted their study, but since the commodities used back then and their assigned weights are unknown, this is not achievable. However, the method itself remains the same as I still use the RICI as a timing signal for the trading strategy. Further, I suspect that the lack of involvement from 20 minor futures contracts will not affect my results significantly. The data on this index are obtained from Rogers International Commodity Indices database on Quandl, and goes back to 31.07.1998. Again, I use weekly Wednesday prices, which provides me with 900 observations. Since the dataset only goes back to 1998, am I not able to replicate the results of Miffre and Basu (2008) all the way back to 1994. Hence, the implementation of my strategy begins in 1998, and is used all the way to the end of 2015.

The "timed momentum" strategy suggested by Miffre and Basu (2008) works in the following way; I go long commodity futures with previous positive returns, if the return on the RICI in the past formation period was positive. In addition, I short commodity futures with previous negative returns, if the return on the RICI in the past formation period was negative.

In general I use the front contracts (#1), as Miffre and Basu (2008) did in their analysis, in both the construction and implementation of the trading strategy. De Groot et al. (2014) however makes an interesting argument about how you can incorporate term-structure information to gain additional risk-adjusted returns. More specific, they identify four reasons to why the futures curve may offer valuable information when exploiting a momentum strategy: contracts further along the curve could (i) exhibit more attractive roll yields, (ii) exhibit lower volatility, (iii) expand the opportunity set of the investible universe and (iv), lower the turnover of the portfolios. They show that momentum strategies that integrate term-structure information, by selecting contracts on the curve with the largest expected roll-yield or with the strongest momentum, earn significantly higher risk-adjusted returns than a traditional momentum strategy. Even though our "timed momentum" strategy does not incorporate this information, this may be of interest for future scientific research.

The momentum strategy is evaluated at a weekly frequency and are based on 1-month holding periods. Miffre and Basu (2008) argue that the ability to time the market phases is dependent on keeping a short holding period (1 month). The different commodities that constitutes the dynamic "timed momentum" portfolio is given equal portfolio weights, to keep things simple. Hence, the portfolio return is the average of the individual commodity returns. Let me illustrate how the trading strategy works by giving a small example:

Table 4: Previous Returns (4-Week Formation Period)

Date	Cotton	Wheat	Gold	RICI
13.05.2015	1.1 %	-1.5 %	1.4 %	3.2 %
20.05.2015	4.2 %	2.8 %	1.8 %	2.4 %
27.05.2015	-2.4 %	0.9 %	-2.0 %	-3.2 %
03.06.2015	0.4 %	6.4 %	-0.4 %	-3.0 %

Table 5: "Timed Momentum" Portfolio

Date	Cotton	Wheat	Gold	RICI
13.05.2015	Go Long!	O	Go Long!	Positive
20.05.2015	Go Long!	Go Long!	Go Long!	Positive
27.05.2015	Go Short!	O	Go Short!	Negative
03.06.2015	O	O	Go Short!	Negative

The returns given in table four are based on a 4-week formation period. That is, the returns in table four is the last month (4 weeks) return rolled one week forward at each row. I consider formation periods of 4 weeks, 12 weeks, 24 weeks, 36 weeks and 48 weeks in this thesis. The timing signal is given to the right, in the RICI column. From table five, you see that I go long previous winners on 13.05.2015, since the RICI return was positive in the formation period. Similar, I short previous losers on 27.05.2015 since the RICI return was negative in the formation period for that row. Hence, the long/short recommendation is created on two signals; the RICI index and the commodity itself. Both of them have to have the same past development before a trading signal is given. This is how this strategy stands out compared to other momentum strategies. The "O" in table five is given when the two signals differ and we don't get a long/short recommendation. In this case, we cancel any previous positions and stay clear from that commodity in the given period.

The level of transaction costs is a key aspect in trading as it can make an otherwise profitable strategy unprofitable if the transaction costs incurred are too high. The number of transactions needed to use this kind of momentum strategy is relative high, which means that the impact of costs on overall profitability could still be substantial, even though transaction costs in commodity futures markets are considerable lower compared to e.g. stocks. That being said, several articles illustrates that the transaction costs in commodity markets are not high enough to change momentum profitability conclusions significantly.

Marshall et al. (2012) finds that commodities from the energy and precious metals sector have lower average trading costs than commodities from the livestock and agricultural sector. Variations within each commodity sector must be expected, however. Further, they find that the average commodity half spread[8] range from 0.035% for trades in the $0 to $100.000 range to 0.044% for trades of $900.000 and above.

De Groot et al. (2014) incorporated three different trading costs schemes in their research to see if any potential excess returns they would find using their momentum strategy was erased by transaction costs. These trading costs schemes reflected both standard and conservative estimates, in addition to a third costs estimate that incorporated trading costs based on liquidity differences in futures contracts. They were able to earn significantly risk-adjusted returns, even after incorporating the three different transaction costs schemes, showing that transaction costs did not wipe out their returns.

[8] The spread is measured as the difference between the settlement price and the quote midpoint prevailing at the time of the transaction.

In addition, Miffre and Rallis (2007) argue that the abnormal returns they identified are not zeroed out by transaction cost, since their strategy minimize trading costs, trade liquid contracts, are not subject to short-selling restrictions, and are less trading intensive than momentum strategies in e.g. equity markets. They did realize that investors who implement their momentum strategies have to post initial margins, monitor margin accounts, roll-over contracts before maturity and pay margin calls. They argued however that the margin calls and the roll-over risk should not be overstated. Since their momentum strategy buys backwardated contracts and sells contangoed contracts, little to no cash will be required for margin calls and hence the roll-over trades will on average be profitable. Nonetheless, they realized that they could not draw a conclusion on the size of the net momentum profits since they did not consider trading costs in their research.

Based on these research papers and the overall perception that transaction costs in commodity markets are practically low in general, I choose to ignore the influence transaction costs may have on my overall conclusion, as I do not suspect it to change my result and conclusion significantly.

Given the nature of how the "timed momentum" portfolio is constructed are we easily able to evaluate its performance following an "out-of-sample" evaluation method. Since the portfolio is constructed entirely on past historic data, can we first use the strategy to create the momentum portfolio, and then see how the portfolio performed given how the market turned out to be. I then calculate average annual returns, Sharpe ratios, and portfolio indexes to answer the research question presented in the introduction.

There is one practical issue the user of this strategy needs to be aware of, and that is that each commodity has several futures contracts with different maturity dates. E.g., the futures on corn expires the business day prior to the 15th calendar day of the contract month. If the strategy gives a "Go Long" signal on corn on 1 May, are you supposed to hold this position for one month. However, you have to exit the original position before four weeks have passed since the contract expires halfway thru the calendar month. What you need to do is to exit the original position in the front month contract, and then "Go Long" again in the back month contract, while the liquidity in the front month contract is still high. This issue does not influence my analytical evaluation of the momentum portfolios since I ignore transaction costs and use a liquidity roll method on the continuous futures data, but in real life, the investor needs to perform an extra transaction when the contract reach maturity.

As mentioned in the introduction, this thesis is motivated by the general need for research to support or reject previous findings. In general, there are several measures you can apply to economic data to make the results more robust. In this case, the robustness of my results are validated by the use of longer time-periods and more data. Further, the use of several different formation periods also contributes to the robustness of my overall conclusion. Hence, I consider my results more robust than the results of Miffre and Basu (2008). However, there is additional robustness measures available, which are not considered in this thesis.

V – Results

My results demonstrate that the performance of the "timed momentum" strategy varies a lot, given the formation period used. There is only one formation period (4 weeks) that generate a negative annual return, while the rest of the formation periods generate positive annual returns. As seen from table six, the 12-week formation period generate the highest annual return. The risk however, measured as annual volatility, is roughly the same across all formation periods.

Table 6: Descriptive Statistics Weekly Data ("Timed Momentum" Strategy Implementation)

Formation Period	Annual Return	Annual Volatility	Excess Kurtosis	Skewness	Maximum	Minimum
4 Weeks	-3.4 %	31.1 %	3.64	0.10	28.2 %	-17.8 %
12 Weeks	22.6 %	31.6 %	2.69	0.34	27.8 %	-15.2 %
24 Weeks	16.8 %	31.6 %	2.75	0.45	27.6 %	-16.2 %
36 Weeks	2.7 %	31.1 %	2.66	-0.20	18.1 %	-26.9 %
48 Weeks	8.4 %	31.9 %	2.86	-0.38	18.1 %	-26.7 %

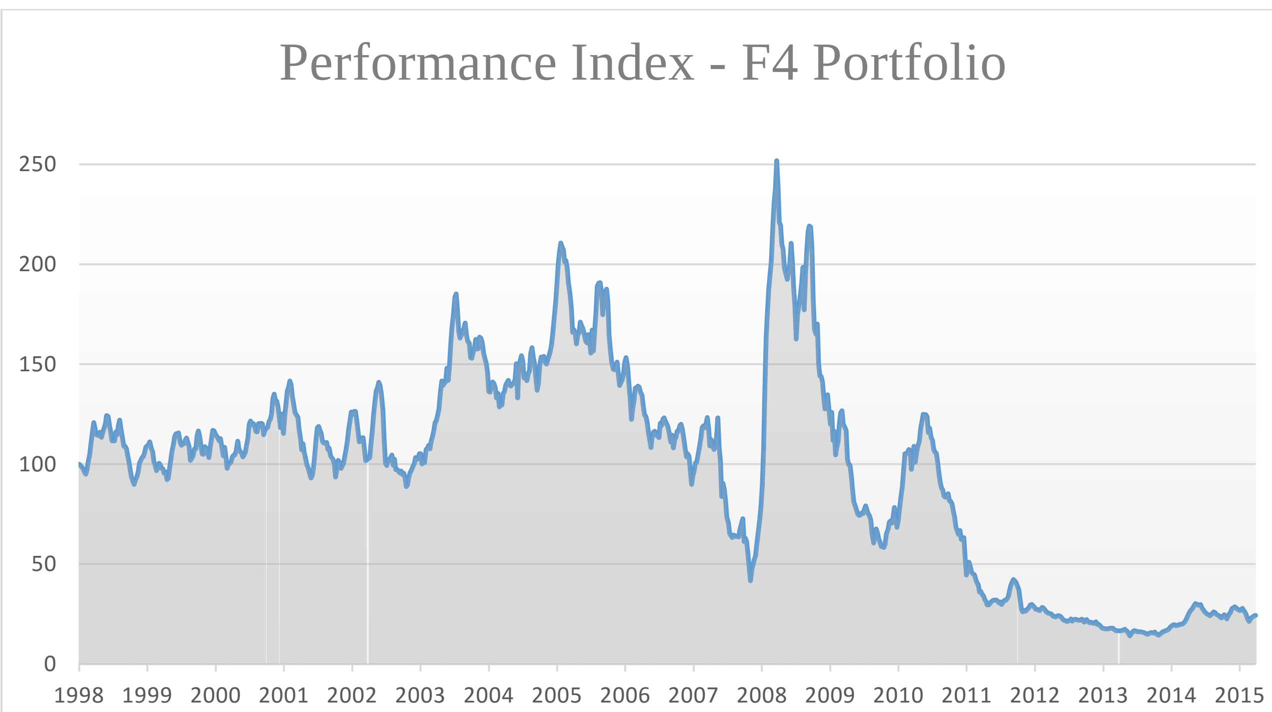
From table seven, we see that the 12-week and 24-week formation period generate significant positive weekly alpha values, in addition to having a negative correlation to the S&P500 index. Further, four out of five formation periods generate positive Sharpe ratios.

Table 7: Regression on Weekly Returns included Sharpe Ratios (X = S&P500, Y = Momentum Portfolios)

Formation Period	**Alpha**	Standard Error	t-value	**Beta**	Standard Error	t-value	**Sharpe Ratio**
4 Weeks	**-0.001**	0.001	-0.400	**-0.095**	0.059	-1.627	**-0.17**
12 Weeks	**0.004**	0.001	3.027	**-0.154**	0.060	-2.565	**0.66**
24 Weeks	**0.003**	0.001	2.274	**-0.207**	0.060	-3.426	**0.47**
36 Weeks	**0.001**	0.001	0.412	**-0.186**	0.060	-3.123	**0.03**
48 Weeks	**0.002**	0.002	1.051	**0.035**	0.062	0.563	**0.21**

V.I – Formation Period: 4 Weeks

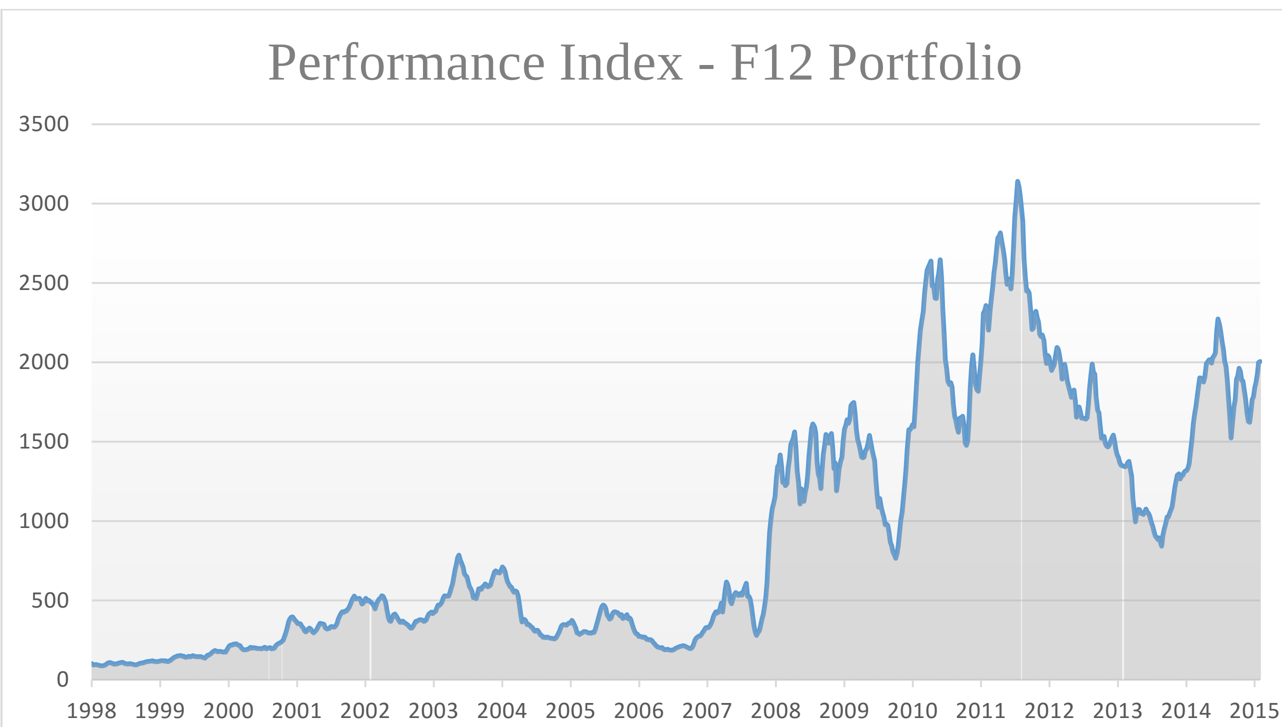
We can see from table six that the "timed momentum" strategy generates an average annual return of -3.4% when it is implemented with a four-week formation period. This is the only formation period considered in the thesis that generates a negative return. As mentioned in the methodology section am I only able to replicate the results of Miffre and Basu (2008) from 1998 to the end of 2007[9]. That time-period generated an annual average return of almost five percent with an average annual volatility of 24%, while my time-period generated an average annual volatility of 31%. When we look at the "performance index" below, we see how the time period Miffre and Basu (2008) considered are characterized by a positive growth, while from 2008 and onwards the performance has been terrible. The weekly alpha value from table seven is statistical equal to zero, which means that the S&P500 index on average has provided the same weekly returns as the momentum strategy given this formation period. Further, we have a negative Sharpe ratio, which is natural since the excess return is negative on average. We also see that this formation period generates the highest excess kurtosis value, which tells us that we observe more extreme returns given this formation period, than in the other formation periods. This can also be shown when comparing the maximum and minimum values from table six with the other formation periods.



[9] Because of the data issues related to the replication of their results, this time-period will from now on be known as "the same time-period as Miffre and Basu (2008)", even though their time-period originally started in 1994.

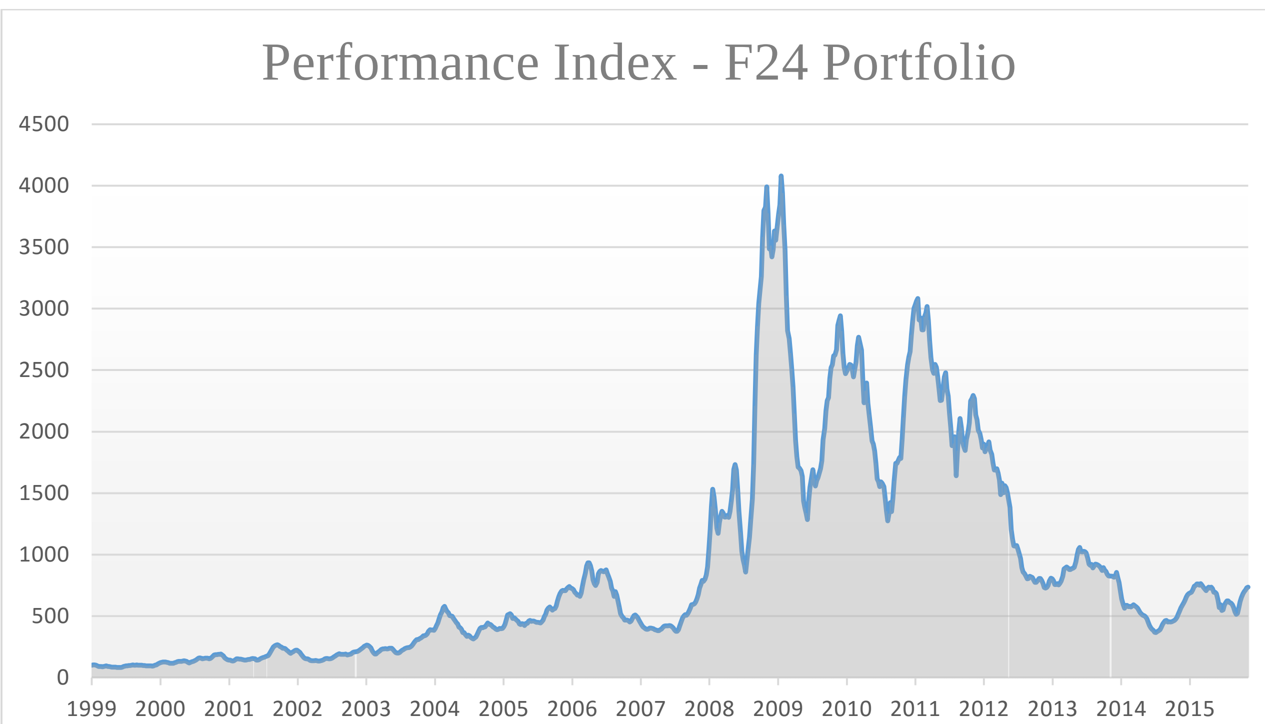
V.II – Formation Period: 12 Weeks

We can see from table six that the “timed momentum” strategy generates an average annual return of 22.6% when it is implemented with a 12-week formation period. This is the highest average annual return generated in this thesis. Interestingly, this formation period has approximately the same level of risk as the 4-week formation period, which generates the lowest annual return. Looking at the “performance index” below, we see that the portfolio experiences substantial volatility from 2008 and onwards, but also a tremendous growth in general. Naturally, the weekly alpha value of 0.4% is both statistical significant and higher than the other formation periods. Further, using this formation period generates a portfolio with a statistical significant negative correlation with the S&P500, and a Sharpe ratio of 0.66. Miffre and Basu (2008) generated an average annual return of 18% with an annual volatility of 26%, using the same formation period. Also, notice how this formation period has one of the highest skewness values, which implies that on average, this portfolio generates a more positive return distribution than the other formation periods. For example, this formation period has one of the highest maximum-values and the lowest minimum-value.



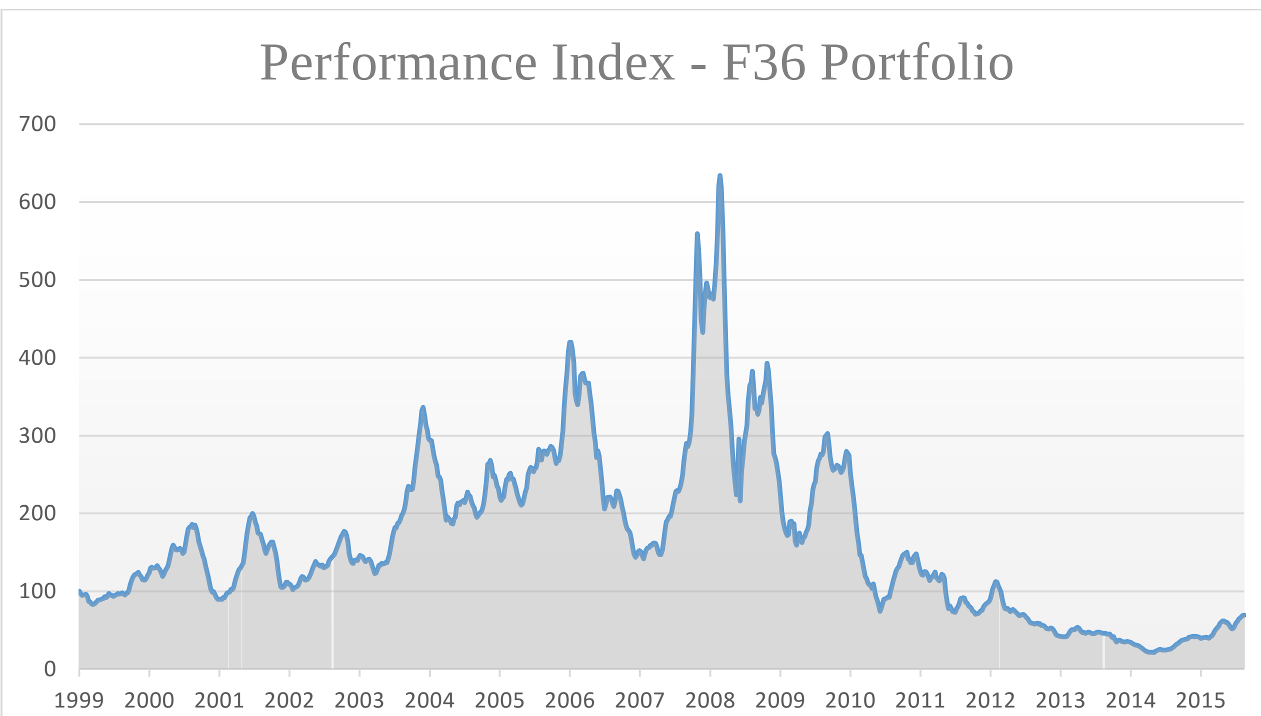
V.III – Formation Period: 24 Weeks

We can see from table six that the "timed momentum" strategy generates an average annual return of 16.8% when it is implemented with a 24-week formation period. This is the second highest average annual return generated. The weekly alpha value of 0.3% is both statistical significant and the second highest compared to the other formation periods. Further, using this formation period generates a portfolio with the most negative correlation with the S&P500, and a Sharpe ratio of 0.47. In addition, this portfolio generates the highest skewness value, which means that no other formation period provides a more positive return distribution than this formation period. Looking at the "performance index" below, we also see that this formation period generates the highest index value recorded compared to the other formation periods. In 2009, the index is well above 3500 before it goes down to under 1000 from the beginning of 2013. Like, the 12-week formation period these index values are enormous. Using the same time-period sample as Miffre and Basu (2008) generates an average annual return of 25% with an annual volatility of 25%, using the same formation period.



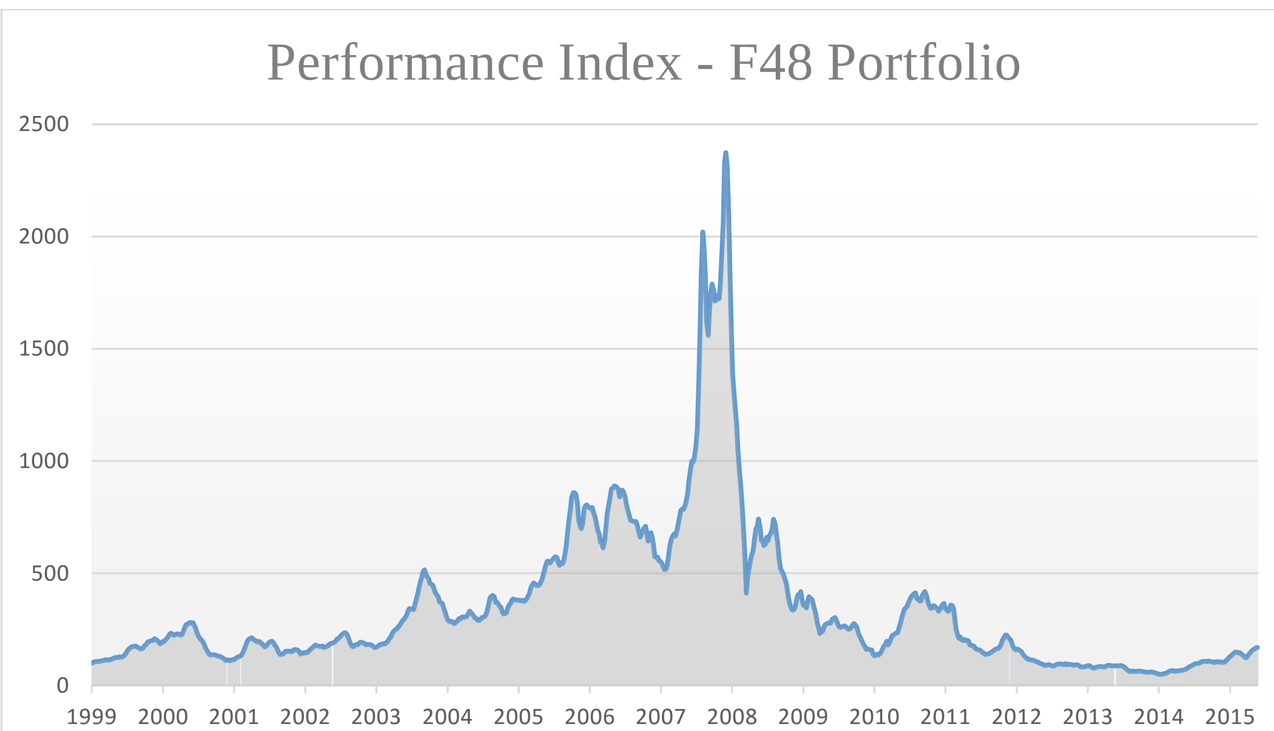
V.IV – Formation Period: 36 Weeks

We can see from table six that the "timed momentum" strategy generates an average annual return of 2.7% when it is implemented with a 36-week formation period. This is the lowest positive average annual return generated. The weekly alpha value of 0.1% is not statistical significant, which means that the S&P500 index on average has provided the same weekly returns as this strategy given this formation period. However, using this formation period yields a portfolio with the second most negative correlation with the S&P500, and a Sharpe ratio of 0.03. Looking at the "performance index" below, we see that this formation period generates lower index values than both the 12-week and the 24-week formation periods. However, this formation period provided a good performance up until 2006, before the trend moved downward after the spike in 2008. Like the four-week formation period, the index is below 100 at the end of 2015. Using the same time-period sample as Miffre and Basu (2008) generates an average annual return of 14% with an annual volatility of 25%, using the same formation period.



V.V – Formation Period: 48 Weeks

We can see from table six that the "timed momentum" strategy generates an average annual return of 8.4% when it is implemented with a 48-week formation period. This is the third highest average annual return generated. The weekly alpha value of 0.2% is not statistical significant however, which means that the S&P500 index on average has provided the same weekly returns as this strategy given this formation period. The positive correlation with the S&P500 is not statistical significant either. The Sharpe ratio is 0.21.
An interesting feature is that the 36-week and the 48-week formation period generates almost the same numbers in table six. Excess kurtosis is almost the same, and both formation periods has a negative skewness. Further, the maximum and minimum values attained are also close to each other. A similar observation can be made between the 12-week and 24-week formation period. Looking at the "performance index" below, we see that the 48-week formation period generates a similar shape as the 36-week formation period. However, we have a much higher spike in 2008 and the index is above 100 at the end of 2015. Using the same time-period sample as Miffre and Basu (2008) generates an average annual return of 29% with an annual volatility of 25%, using the same formation period.



As mentioned, several of the index values in the performance graphs are extremely high and some may argue that these spikes are not realistic or that the probability of experiencing them are very low. However, if you had followed this strategy, independent of the formation period, you would have come across them and hence been in a position to profit from them.

It is also interesting to compare my time-period results with the results generated when considering the same time-period as Miffre and Basu (2008) did. First, notice how the average annual volatility were about five to six percentage points lower in their time-period, but still stable across different formation periods like now. Second, all of the formation periods generated a positive average annual return, while using the 4-week formation period in my time-sample generated a negative average annual return. Third, the average annual return was in general higher in their time-period than in mine. In addition, the formation period used to generate the highest annual return as changed from 48 weeks to 12 weeks. Higher volatility, which gives shorter trends, among commodities may be the reason to why we observe this. The different results generated, given the formation period used, can also be further evidence of the "behavioral hypothesis". These replicated results are given in each respective formation period subsection above, in addition to the table below.

Table 8: Comparison of Descriptive Statistics Weekly Data

	Miffre and Basu (2008) 1998 – 2007		Full time-period 1998 – 2015	
Formation Period	Annual Return	Annual Volatility	Annual Return	Annual Volatility
4 Weeks	4.8 %	24.3 %	-3.4 %	31.1 %
12 Weeks	17.8 %	26.0 %	22.6 %	31.6 %
24 Weeks	24.9 %	25.0 %	16.8 %	31.6 %
36 Weeks	13.8 %	25.2 %	2.7 %	31.1 %
48 Weeks	29.0 %	25.2 %	8.4 %	31.9 %

To summarize, using 12, 24, and 48-week formation periods has generated high average annual returns in this time-period. However, the 48-week formation period portfolio did not generate a statistical significant higher annual return than the S&P500 index. Hence, given these results, only the 12- and 24-week formation period is recommended when using the "timed momentum" strategy. In addition to generating a higher average annual return than the S&P500 index, these formation periods also beat the RICI. This provides us with further evidence that long/short trading strategies are superior over long-only strategies. However, with an average annual volatility of over 30%, this trading strategy is not for the risk-averse investor.

VI – Conclusion

This objective of this thesis is to answer the research question; given additional and newer data, is the "timed momentum" strategy proposed by Miffre and Basu (2008) still profitable?

We see from table six that the simple answer is yes. The two portfolios with 12 and 24-week formation period has delivered high average annual returns, statistical significant alpha values, and positive Sharpe ratios. Hence, given market data from the time-period from 1998 to the end of 2015, the "timed momentum" strategy proposed by Miffre and Basu (2008) does indeed still provide abnormal returns when implemented with the two formation periods mentioned above. This is in spite of the fact that I use fewer commodities and maybe a different timing signal in the implementation of the "timed momentum" strategy than what Miffre and Basu (2008) did. The success of the "timed momentum" strategy shows the superiority of long/short strategies over long-only strategies. However, remember that past performance does not guarantee future performance.

All the formation periods generated positive and large annual returns in the study of Miffre and Basu (2008). This is not the case now that we consider a longer time-period sample. The average annual returns are in general smaller now. In addition, the general risk associated with this trading strategy has risen with roughly five to six percentage points. The underlying reasons to why momentum strategies provides abnormal returns are still up to debate as support of both behavioral explanations and rational pricing explanations has been brought forward.

One of the weaknesses of this study is that I do not consider transaction costs. This is not suspected to change the overall conclusion that the "timed momentum" strategy is still profitable. However, we are not able to see the correct magnitude of these returns before transaction costs are considered. This can be an area for further research. In addition, I could have used additional robustness tests to the data. Another field of further research is to find, if any, the "optimal" formation period. Both mine and the results of Miffre and Basu (2008) shows changes in average annual return given the formation period considered. Hence, it would be interesting to see if there is a formation period that provides a significant higher return than those formation periods considered here.

The “timed momentum” strategy (presented in detail in the methodology section) is very practical and hands-on in the sense that you do the same when implementing it in real-life, as I did in excel to generate these results. In addition, the strategy is quite easy to understand and straightforward, and the data is downloaded for free from Quandl. You simply look at the past performance of both the individual commodities and the commodity index, to decide which commodities that will constitute your portfolio.

These are the benefits when implementing the strategy in real-life. However, this trading strategy is probably more suitable for institutional investors and hedge funds than private speculators. There are several reasons for this but the biggest is that you need a considerable amount of capital to be able to gain access to, and take positions in, all of the commodities considered in this thesis. However, if you have access to these futures contracts as a private investor, either directly thru the exchange or indirectly thru CFD’s or ETF’s, there is no problem to implement this strategy. But, in real-life, you have to remember to track the maturity dates of each individual futures contract more closely as mentioned in the methodology section. In addition, you have to consider transaction costs, initial margin, margin calls, monitoring costs etc., but this applies for all trading strategies and not the “timed momentum” strategy in particular.

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Disclaimer

This thesis should in no way be interpreted as an unconditional recommendation to buy or sell financial products. Any potential investment must be seen in conjunction with your financial situation, knowledge and experience with financial instruments. All investments will typically be subject to risk, and the monetary value of any investments may rise as well as fall. I do not undertake any responsibility for losses or expenses suffered from the use of the information in this thesis.

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