Master thesis

Systematic Investment Strategies in Futures Markets

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Management Summary

Futures have been expanding rapidly since the rise in investment inflow into index funds around 2003 and represent a crucial investment instrument. Investors use futures markets for speculative or hedging purposes. The Commodity Futures Trading Commission is the regulatory body of the futures market, and one of their missions is to help the public to understand the market dynamics of futures markets. To do so, they publish the Commitment of Traders reports, which is a breakdown of the open interest (outstanding contracts) of the traders in the long and short position of different classifications.

The goal of this thesis is to research the effect of the change in the reallocation signal from momentum and carry strategies, as well as the first differences of the VIX index and the inverse volatility, onto the change in the positions of traders. The existing literature in this context focuses on the relationship between returns, volatilities and the positioning of traders as well as the relationship between the classifications themselves. We found that the research question that we examined has yet not been researched.

We focused on 33 US futures markets, where 22 were commodities, seven were currencies, and four were US fixed income. We also estimated the effects on four different Commitment of Traders classifications and compared the results with each other. We evaluate four classifications since the newer classifications provide a more detailed breakdown of the speculative category.

In our empirical results, we first compared the performance of the momentum, carry, and long-only strategies, where we found that the momentum strategy performed best across all markets. The carry strategy performed best in the energy and agricultural sector, as well as partly in the currency and fixed income markets. The long-only strategy was able to outperform both strategies in the fixed income market as well as the commodity sector of metal futures. In a secondary analysis, we looked at the movement across the markets and found that futures which belong to the same sector or market have a higher correlation.

In the statistical analysis, we estimated multiple regression models to measure the effect of the reallocation onto the change in the position of the traders. In summary, we accepted

the null hypothesis, that there is a significant effect on the reallocation signal of the momentum strategy for commodity and some currency futures, in all classifications. For the reallocation signal from the carry strategy, we accepted the null hypothesis for agricultural futures in the classification of non-commercial traders and managed money, but declined it for all other classifications.

Preface

I want to thank Prof. Dr. Peter Schwender for his excellent and conscientious support during the whole work. Further, I would like to thank Dylan Schmitter, John McHughan, and Paula Isacson for helpful comments and suggestions during the writing process, as well as my family and friends. Last but not least, I would like to thank the team of Balance of Payments and Swiss Financial Accounts from the Swiss national bank for the interesting inputs during the lunch breaks.

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List of abbreviations:

COT	Commitments of Traders
CFTC	Commodity Futures Trading Commission
CTA	Commodity Trading Advisors
DCOT	Disaggregated Commitments of Traders report
TFF	Traders of Financial Futures

1 Introduction

The introduction lays the foundation of the thesis and explains the objectives, research questions, hypothesis, and procedure.

1.1 Initial Situation

In general, futures, particularly commodity futures, are excellent portfolio diversifiers, and for some, commodity futures are an effective hedge against inflation according to Bodie and Rosansky (1980). Futures also offer leverage, and they are not subject to short-selling restrictions. Additionally, the nearby contracts are typically very liquid and cheap to trade. For all these reasons, commodity futures are good candidates for strategic asset allocation and have proven to be useful tools for alpha generation. [2]

The regulatory body of the futures market is the Commodity Futures Trading Commission. Their mission is to foster open, transparent, competitive, and financially sound markets and to protect the users from fraud. Additionally, their mission is to give the public a better understanding of the futures market. To do so, they publish different Commitments of Traders reports which provide a breakdown of the weekly open interest, in the long and short position of different classifications. This data has attracted many researchers and professionals to research the effects of the positioning of the traders on different variables from the futures market. During our literature review, we found that the effects of the change in trading signals have on the positions of the speculative traders had not yet been explored more precisely, the effects of the change in trading signals on the position of the speculative traders. We examined this effect on 33 US futures markets, where 22 were commodities, seven were currencies, and four were US fixed income and use trading signals from momentum and carry strategies.

Our motivation for this thesis is to contribute to the literature in examining a research question that has not yet been researched. Moreover, we are interested in the results across different classification and to do so do we further estimated the effect on different classification and compared the results.

1.2 Problem Definition and Research Question

One of the missions of the commodity futures trading commission is to help the public understand the market dynamics of futures commodity markets (see chapter 2.1). In this thesis, we continue this mission by focusing on trading strategies and the effect of the change in the trading signal on the change in the position of speculative traders. The goal of speculative traders is to generate excess returns, and thus investment strategies play a significant role. In this thesis, we examine two investment strategies, namely, momentum and carry strategies (see chapter 3.2).

More precisely, we focus on the change of positions, because we assume that a change in a trading signal leads to a lagged reallocation of the traders' position for a given market. Hereafter, we build the following hypotheses, where H_0 is the null hypothesis and H_1 is the alternative hypothesis:

H_0: The reallocation of a position, due to a change in the trading signal has a significant effect on the aggregated change of the net trading position.

H_1: The theoretical reallocation of a position due to a change in the trading signal has no significant effect on the aggregated change of the net trading position.

We also examine the effects of a change in the inverse volatility and the first difference in the VIX index. The VIX index is a global variable, meaning it is the same for every futures market, and it has been used in other studies as a proxy for the risk appetite for financial traders (Kang et al. (2017), and Cheng et al. (2012)). The inverse volatility can be used as a tool to weight the assets in a portfolio. We examine if the change in the inverse volatility can explain the change in the traders' position.

1.3 Objective

First, we summarize studies which have also researched the effect of speculative traders on the market dynamics and investment strategies in futures markets. Further, we examine the various classifications of traders to gather an overview of which positions are relevant for our specific research question. The goal of this section is to have an in-depth understanding of the classifications of traders, as well as an understanding of the futures market, and the investment strategies. Second, we focus on collecting the necessary data and processing it to a level where it can be used for the analysis. Third, we analyze how the trading strategies perform in the different markets and how the dynamic is between different key measurements in the classifications. We estimate the effect of reallocation signals due to a change in the trading signal on the change of the traders' position. Overall the aim is to find evidence to accept or reject our null hypothesis and to contribute to the research of the dynamics of traders in futures markets.

1.4 Structure of the Thesis

The Thesis is organized as follows. Chapter One provides an introduction to the topic and states the scope of the thesis. Chapter Two provides a summary of the classifications by the CFTC and an overview of the relevant literature. Chapter Three shows how we processed the data, calculated the trading strategies, transformed the trading signals and the raw data from the CFTC to get meaningful variables, as well as the definitions of the model which we used. Chapter Four presents an analysis of the data and the results from the estimations. In Chapter Five, we present the results and the key findings and draw our conclusion.

2 Literature Review

In chapter 2.1, we are first evaluating the different COT reports and the role of the commission in the futures market and decide which classifications we are going to investigate more in detail. In chapter 2.2, we provide a summary of recent studies that researched the effect of the traders' position and volatility, returns, and prices.

2.1 The Classification of the Traders by the CFTC

The Commodity Futures Trading Commission (CFTC) was founded in 1974 with the enactment of the Commodity Futures Trading Commission Act. Their mission is to foster open, transparent, competitive, and financially sound markets. The commission aims to protect market users and their funds, consumers, and the public from fraud, manipulation, and abusive practices related to futures, derivatives and other products that are subject to the Commodity Exchange Act. Additionally, their mission is to give the public a better understanding of the futures market. To do so, they started to publish a legacy Commitment of Traders report (COT). In the beginning, they released the reports monthly but switched to mid-and month end in 1990, to every two weeks in 1992, and from then on to weekly, due to the growth and the complexity of the industry. [5]

With the increasing complexity and growth of the futures market, they improved the reports and added more detailed classifications to improve their report. The CFTC has of today four main COT reports (Legacy Report, Supplemental Report, Disaggregated Report, and the Traders in financial futures Report), which we briefly summarize in the following paragraphs.

<u>Legacy Commitments of Traders report</u>

The “Legacy Report” is the first COT report that has been published by the CFTC. It provides a break down of the reportable open interest positions into two classifications: non-commercial and commercial traders. Whereas the open interest breakdown is in long short and spread positions. For the understanding of what that means, we explain the following terminologies: open interest, reportable traders and the difference of commercials and non-commercial traders.

The open interest is defined as the total of all outstanding futures, which are not yet offset by a transaction. Further is the aggregate of the long open interest equal to the sum of the short open interest. Note, that only the participants who are identified as reportable traders have to report to the CFTC and have to file a daily report with the commission. Those reports show the futures and options positions of traders that hold positions above specific reporting levels. The current reporting levels are stated in CFTC Regulation 15.03(b).[1] The aggregate of all traders' positions reported to the Commission usually make up 70 to 90 percent of the total open interest in any given market. The Commission, as the regulator of the market, has the freedom to lower or raise the reporting level to strike a balance between collecting sufficient information and overseeing the markets. To classify the traders, they define the commercial traders, and all other traders are therefore non-commercial traders. Commercial traders are identified as such when they use the futures market to hedge the risk in the underlying business. It is also possible that a trader classifies as a commercial trader in some commodities and as a non-commercial trader in others[2] [5]

Supplemental Commitments of Trades Report

Supplemental reports were first published at the beginning of January in 2007. This report provides a breakdown of the reportable open interest positions. Where they classify the traders in three groups: non-commercial, commercial, and index traders. Index traders are defined as an entity that conducts futures trades on behalf of a commodity index fund or to hedge commodity index swap positions. [6]

Disaggregated Commitments of Traders Report

The CFTC began publishing a Disaggregated Commitments of Traders report (DCOT) on 4th September 2009. The DCOT report increases the transparency form the legacy COT reports by separating the traders in four groups. The first category consists of traders who are either identified as producer, merchant, processor, user, the other categories are swap dealers, managed money, and other reportable traders.

[1] Link tot he CFTC Regulation 15.03(b): https://www.ecfr.gov/cgi-bin/retrieveECFR?gp=&SID=970471b8455f4bab7db4110cfde50731&mc=true&r=SECTION&n=se17.1.15_103 , opened on the 31. May 2019

[2] More in detail definitions are provided by the CFTC by: https://www.cftc.gov/MarketReports/CommitmentsofTraders/ExplanatoryNotes/index.htm

The first category (Producer/ merchant/ processor/ user), as well as swap dealers, use the futures market to hedge the risks associated with their activity. Money managers can be registered Commodity Trading Advisors (CTA), registered commodity pool operator or an unregistered fund, according to the CFTC. These traders are engaged in managing and conducting organized futures trading on behalf of clients. [7]

Traders in Financial Futures

Traders in Financial Futures (TFF), is a report that improves the transparency of the participants in the financial futures market. This report has been implemented in the COT reports in 2009. The new report separates large traders in the financial markets into the following four categories: Dealer/ intermediary, asset manager/ institutional, leveraged funds, and other reportable traders. The TFF report classifies the traders into the buy- and sell-side. The category dealer/ intermediary build the buy side because they earn commissions on selling financial products, capturing bid/ offer spreads and otherwise accommodating clients. The remaining three categories represent the sell-side, because they use the markets to invest, hedge, manage risk, speculate or change the term structure or duration of their assets. Pension funds, endowments, insurance companies, mutual funds, and those managers whose clients are mostly institutional, are classified as asset manager/ institutional. Hedge funds and various types of money managers, including registered commodity trading advisors (CTAs), are classified as leveraged funds. The strategies of those may involve taking outright positions or arbitrage within and across markets. The traders may further be engaged in managing in trading futures on behalf of speculative clients. [8]

After taking a look in at the classifications of traders, we filter for groupings which contain speculative traders. We decided that we want to analyze the classification of non-commercial traders from the Legacy Report, which contains the position of the traders for every futures market. For commodity futures, we also analyze the position of managed money from the DCOT, because this classification includes CTAs as well as funds, which both are likely to use trading strategies. For the financial futures, we further regard the classification of levered funds and asset managers from the TFF, the reasoning is the same as above, we assume that traders in these classifications use trading strategies.

2.2 Relationship between Traders Position and Other Variables

In the chapter above, we explained the classifications of the traders by the CFTC. These available public datasets fueled researchers to find connections between the prices, returns, volatility, and the positioning of the traders, where they also researched the reverse influence. In the following paragraphs, we provide a summary of the findings of these researchers and the gap that we are investigating in this thesis.

By examining the relationship between hedgers and speculators found the researchers Kang et al. (2017), that the short-term position changes are mainly driven by impatient speculators, while the hedging demands from commercial traders primarily driven from longterm variation. Moreover, they found that hedgers provide short-term liquidity to speculators. [3]

Relationship Between Trading Activities and Prices, Returns, and Volatility

The researchers Mayer et al. (2017) provide an evaluation of studies, which researched the potential effects of the lead-lag relationship, on futures trading activity of commercial and non-commercial market participants and futures prices and volatility in various commodity markets. The results of that summary are that the lead-lag relationship can be influenced positively (increasing trading volume is destabilizing and leads to increasing volatility) or negatively (increasing trading volume is stabilizing and leads to decreasing volatility). Some of the evaluated studies reject both hypotheses, as no significant influence of trading position on either the volatility nor the price could be found. Some of the studies test the reverse causality, meaning that changes in prices or volatility cause a shift in the traders' positions and found that it could lead to more complete results. In summary, they found that the numbers of studies that support the hypothesis that the trading activity may influence volatility are similar to the number of studies, that rejects that hypothesis. Regarding prices, only a few studies, which mostly used short time frames, and were dependent on other restrictions, found an indication for a significant relationship.[9]

For example, the researchers Sanders et al. (2004), by examining the positions of non-commercial and commercial traders in the energy futures market, a positive correlation between returns and positions held by non-commercial traders. Moreover, they found that positive returns lead to an increase in the non-commercial net position in the following week. However, they could not found that traders' net position lead to market returns in general. [10]

The researchers Mayer et al. (2017) themselves focused on commodities in the sector of metal and found that there is hardly any influence of trading activities driving spot prices in the long term, but rather stimulating the volatility to some extent. Moreover, they find that there is strong evidence that commodity prices and volatility drive the trading position. [9]

Cheng et al. (2012) analyze the joint responses of and positions of commodity index traders and hedge funds, in the commodity futures markets to movements in the VIX. By jointly analyzing positions and prices, allows them to examine whether amplification effects due to distressed financial institutions or hedging pressure are also at work. Their finding is that speculators (Commodity index traders and hedge funds) positions react negatively to the VIX during the recent financial crisis. [3]

COT Positions to Predict Price Changes and Returns

Most of the studies that tried to predict the change in prices or returns based on the shift in the position of the traders could not find significant statistical predictability.

Alquist and Gervais (2013) used the public COT Reports to measure net positions of commercial and non-commercial traders and found that changes in either category could not predict monthly changes in oil prices or the futures-spot spread over 2003-2010, though there was statistically significant predictability when the sample was extended back to 1993. Neither could the researchers Hamilton and Wu (2014) found evidence that the positions of traders in agricultural contracts identified by the CFTC as following an index strategy can help predict returns on the near futures contracts.

On the other hand, Singleton (2013) was able to predict oil prices. He examined the impact of investor flows and financial market conditions on returns in crude oil futures markets, that by considering the imperfect information about real economic activity, including supply, demand, and inventory accumulation, and speculative activity in oil markets, helped them to predict weekly and monthly returns on crude oil futures contracts over September 2006 to January 2010.

Overall, we found that the literature review about futures markets and the studies about variables that might influence the price is vast. Moreover, we found that there is limited evidence that the traders' positions can be used to generate returns or explain the market. In the end, we did not find a study that examines the effect of the change in the trading signals (reallocation signal) on the traders' position. In this thesis, we research this effect and try to contribute to the literature of the futures market by closing the gap that yet not has been studied.

3 Methodology

In the chapter above, we examined the existing literature and found no study that examines the effect of reallocating a position in the market due to a change in the trading signal on the position of the traders, in a similar way. We derived a null hypothesis, which is, that the reallocation of the positions due to a change of the trading signal affects the position of speculative traders. Based on an empirical investigation, the hypothesis is tested, and the empirical results are stated in chapter 4. The empirical investigation aims to analyze the possible effect of the reallocation on the volumes of the trades. This chapter deals with the methodology and describes the preparation of the data as well as how the data was used.

3.1 Subject Matter and Period of Investigation

In the following subchapters, we summarize the used dataset and the time horizon, which we regarded in this thesis. The whole data set is obtained from Bloomberg. Bloomberg is a private company that processes financial news and information. Bloomberg provides real-time data, economic news, historical price information, fundamental data, and analyst assessments.

3.1.1 COT Positions

Our variable of interest to explain is the positioning of the traders; The CFTC publishes this variable in the COT reports. Since the reports are work in progress and the classification became more precise over time, we focus on four classifications from three reports. For commodities futures, we analyze the class non-commercials from the legacy COT report and the class of managed money from the DCOT report. For the financial futures (currency and fixed income) we focus as well on the non-commercial traders, the class of levered funds and the asset managers, the latter two classifications are both from the TFF report. The period of research is for the non-commercial traders is from

November 11, 1997, to February 26, 2019, and for all the other classifications from June 20, 2006, to February 26, 2019.[3]

3.1.2 Futures contracts Data

The data comprises of 33 US futures contracts. Of the futures contracts, 22 are commodities, seven are currency, and four are US fixed income futures. We consider more precisely the following futures:

Commodities. Eleven agricultural futures (cotton #2 [CT1], coffee 'C' [KC1], sugar #11 [SB1], frozen orange juice [JO1], cocoa [CC1], soybeans [S1], corn [C1], soybean oil [BO1], soybean meal [SM1], wheat [W1] and wheat, #2 hard winter [KW1]) four livestock futures (feeder cattle [FC1], live cattle [LC1], aswell as lean hogs[LH1]) 4 metal futures (gold [GC1], silver [SI1], platinum[PL1], copper, high grade[HG1]) four oil and gas futures (crude oil, light sweet[CL1], RBOB gasoline [XB1], natural gas (henry hub) [NG1], and heating oil [HO1])

Currencies. British pound [BB1], Euro FX [EC1], Canadian dollar [CD1], Australian dollar [AD1], Japanese yen [JY1], New Zealand dollar [NV1] and Swiss Franc [SF1]

Fixed Incomes. We examine two, five and ten-Year US T-Notes[TU1, FV1,TY1], as well as a 30- year US T Bonds [US1]

The abbreviation in the square brackets is the ticker symbol from Bloomberg; the number one stands for the first generic futures contract. In the analysis, we will for space reasons generally use the tickers symbols. In the Appendix (chapter 7.1) is an overview of the data in the form of a table with the source of the data.

[3] An overview of the data is provided in the Appendix chapter 7.1

3.2 Trading Signals

In this section, we first describe the construction of the time series momentum and carry strategies of the different asset classes. In the next step, we evaluate the statistical framework which will be used to explain the research question.

3.2.1 Time Series Momentum Strategy

We focus here on a time series momentum strategy, which does not diversify over different asset classes. The base model is based upon the works of Moskowitz et al. (2012) and Elaut and Erdos (2016). The only differentiation we do is that we look at each asset class independently and do not build a portfolio, as they suggest, because we try to estimate the effect of the change in the trading signal on the traders' position for every futures market separately. Analytically, a traditional TSMOM strategy with a look-back period of n days is defined as

$$r_{t,t+1}^{TSMOM} = sgn\left(r_{t-n,t}\right) * \frac{\frac{0.4}{\sqrt{261}}}{\sigma_t} * r_{t,t+1} \tag{1}$$

Where *sgn()* denotes the signum function, whereas the output is the trading signal which can take the values of plus one or minus one. The value of plus one indicates a buy signal and minus one a sell signal. The daily excess return is defined $r_{t,t+1} = \frac{F_t - F_{t-1}}{F_t}$. Moskowitz et al. estimate the ex-ante volatility as σ_t for each point in time, with a simple model: The exponentially weighted lagged squared daily returns. Calculated with a rolling window of sixty days. For every futures contract, the daily volatility is calculated with the following model:

$$\sigma_t^2 = \sigma_{T-60,T-1}^2 = (1-\lambda)\sum_{t=0}^{60} \lambda^t \left(r_{T-t-1} - \bar{r}\right)^2 \tag{2}$$

For the parameter λ, Moskowitz et al. chose it so that the center of mass of it is approximately sixty days. Moskowitz et al. also chose a correction factor of 40% in equation 2, since it makes it easier to compare volatilities across different assets classes and it is similar to the risk of an average individual stock. As a result, they get a performance return for each point in time.

Elaut and Erdos (2016) extended the base model to an "adaptive time series model". Where they average the signal for any given futures contract over a wide set of look-back horizons, they excluded lookback periods of less than ten days. The reason for the exclusion is that trading within such short intervals probably involves models which are not based on daily closing prices. They developed the model to calculate the performance returns for a portfolio. The adjusted version of the model for only one security is:

$$r_{T+1}^{ATSMOM} = sgn\left[\frac{\sum_{t=10}^{260} sgn\left(r_{T-t,T-1}\right)}{251}\right] * \left[\frac{0.4/\sqrt{261}}{\sigma_{T-60,T-1}}\right] * r_{T+1} \tag{3}$$

The result from equation (3) is a performance return, that consists of a signal, which tells us if we should buy or sell, a risk metric (volatility) and the future return. Note that the signal strength is the value we get in the bracket and the buy or sell signal is the *sgn*[] of the signal strength.

The main difference to the base model is that they consider many lookback periods. The signal strength for every futures contract will vary between minus one and plus one. A positive aspect is that when a trend starts to fade, the short term signal will force the strategy to lower the exposure quicker than a momentum strategy, that only considers a long term signal. In that perspective, their model is more "adaptive" than a standard time series momentum model.

The results from Elaut and Erdos show that the ATSMOM matches several stylized facts (market risk-, size-, value-, liquidity factor) of manager-based indexes better, than existing benchmarks and outperforms those benchmarks in explaining the returns of CTAs.

It is relevant for us in this thesis how they calculated the buy or sell signal (see equation 3). By comparing the strategies, later on, we focus on the traditional measures of cumulative excess returns and mean excess returns, as well as volatility, Sharpe ratios and to describe the distribution of the returns we use kurtosis and skewness. (see chapter 4.1.1).

3.2.2 Carry Component of Returns

To calculate the carry component of the futures returns, we differentiate between the asset classes. To calculate the carry component, we follow Koijen et al. (2016). Their definition of carry and how they use this definition to describe the carry of different asset classes will be explained in the following subchapter.

3.2.2.1 Carry as a Characteristic of Every Asset Class

According to Koijen et al. (2016), a carry is the return on a futures position when the price stays constant over the holding period. In their paper, they examined different asset classes and defined a uniform futures-based definition of carry. They describe the base model for carry as follows:

$$C_t = \frac{S_t - F_t}{X_t} \tag{4}$$

The assumption is that the spot price stays the same over time, meaning that the spot price at t is the same as the spot price at $t + 1$. Under this assumption, $F_{t+1} = S_t$ since the futures price expires at the future spot price ($F_{t+1} = S_{t+1}$). X_t is the investment that is allocated to finance each futures contract. In connection to equation 4, X_t is a scaling factor, which can be chosen freely. In their analysis the computed returns and carry based on a "fully collateralized" position, meaning that the amount of capital allocated to the position is equal to the futures price, $X_t = F_t$. Special about carry is that it is a model-free characteristic that is directly observable ex-ante from futures (or synthetic futures) prices.

Later on, we will use the terminologies of backwardation and contango. Where a term structure of futures is in backwardation if the futures prices rise with an approaching maturity. Therefore is the term structure of a futures contract is in contango if the prices decrease with approaching maturity. [17]

3.2.2.2 Currency Carry

Koijen et al. (2016) define the currency carry as the investment in a currency by literally putting cash into a country's money market, which earns the interest rate if the exchange rate does not change. That means the futures price can be defined as $F_t = S_t \frac{1+r_t^f}{1+r_t^{f*}}$. Therefore is the no-arbitrage price of a currency forward contract with spot exchange rate S_t, where r^f is the local interest rate, and r^{f*} is the foreign interest rate. They define the carry of a currency as:

$$C_t = \frac{S_t - F_t}{F_t} = \left(r_t^{f*} - r_t^f\right) * \frac{1}{1 + r_f} \tag{5}$$

It implies that the carry of investing in a currency is the interest-rate spread, adjusted with a scaling factor $\left(\left(1 + r_t^f\right)^{-1}\right)$ that they chose to be close to being one, thus the carry of a currency is the foreign interest rate in excess of the risk-free local rate. Due to the illiquidity of FX-futures, we use forward points to determine the forward rate and therefore, the carry of currencies.[4]

This leads us to the following two scenarios:

Forward premium: Forward price in the future will be *higher* than the spot price. Thus the forward curve is in contango, and we would take a short position for that futures to benefit from the negative carry.

Forward discount: Forward price in the future will be *lower* than the spot price in the future if the spot price does not change. Thus the term structure is in backwardation, meaning that we would take a long position in the market and earn from the positive carry.

[4] Definition of forward points: Forward points are basis points, which are either added or subtracted to the current spot price of a currency pair to determine the forward rate for delivery on a specific value date. When the points are added it is called a forward premium. If they are subtracted it's a forward discount.[18]

3.2.2.3 Commodity Carry

The no-arbitrage of a commodity futures contract is defined as $F_t = S_t\left(1 + r_t^f - \delta_t\right)$, according to Koijen et al. (2016). In this formula δ_t is the convenience yield, which in other words is the implied yield on inventories. We can transform the equation for the futures price to calculate the carry of commodities, shown in equation (6).

$$C_t = \frac{S_t - F_t}{F_t} = (\delta_t - r^f)\frac{1}{1 + r^f - \delta_t} \tag{6}$$

According to equation 6, The commodity carry is the expected convenience yield of the commodity in excess of the risk-free rate. Since spot prices can be illiquid, we use two futures contracts, which has a soon expiry. To compare the carry of different asset classes or within the commodities, we further scale the carry signal to one year. Which leads us to the following carry formula:

$$C_t = \frac{F_{t,i} - F_{t,j}}{F_{t,j}} * \frac{\Delta t}{360} \ , \qquad i < j \tag{7}$$

Note that the contract settlement date of i has to be smaller than j and that Δt is defined as the time difference between the settlement dates between j and i. When the carry is positive, it means the futures term structure is in backwardation.

3.2.2.4 Fixed Income Carry

When applying a consistent definition for finite-maturity securities such as bonds, treasuries, or options, special care must be taken, according to Koijen et al. To be precise, they define the carry C_t^τ for treasuries at time t with τ periods to maturity as

$$C_t^\tau = \frac{S_t^{\tau-1} - F_t^\tau}{F_t^\tau} \tag{8}$$

$S_t^{\tau-1}$ is the spot price of a security with $\tau - 1$ periods to maturity. The primary issue is that the assumption of constant spot prices is not reasonable anymore, because the bond value to maturity are known in advance and are most likely not equal to the current value.

The problem is that liquid bond futures contracts are only traded in a few countries, and if they exist, in most cases only the first–to-expire futures contract is liquid. With zero coupon or US Treasury bills yield y_t^τ for a bond with τ periods to maturity at time t, the spot price is given by $S_t^\tau = \frac{1}{(1+y_t^\tau)^\tau}$. Moreover, is the one-period futures price for a contract is given as $F_t^\tau = \left(1 + r_t^f\right) S_t^\tau$. Applying the carry definition (equation (8)) with a simple approximation based on the bond's modified duration, D^{mod} we come to a more useful carry definition:

$$C_t^\tau \cong \left(y_t^\tau - r_t^f\right) - D^{mod}\left(y_t^{\tau-1} - y_t^\tau\right) \quad (9)$$

Equation 9 shows that the carry consists of two effects:

1. The bond's yield spread to the risk-free rate, which is called "slope" of the term structure. In this thesis, we focus on the slope and take it as our carry.
2. The "roll down" captures the price increase because the bond rolls down the yield curve.

Another way to look at the carry of treasuries is if we compare the yields of the US treasuries and the 3M US libor. Where the general case is that the treasuries yields are higher than the libor yields, if the libor yields are higher than the treasury yields, then the yield curve is inverted, and an investor would preferably invest in the money market rather than the treasuries. Therefore we focus on the slope of the term structure and derive the carry from that component.

3.3 Volatility Index and Inverse Volatility Strategy

This chapter provides evidence on why a global measure for risk appetite could be useful for the later statistical modeling when we try to estimate the effect of reallocation on the change in a net long position of the traders. Moreover, we introduce an inverse volatility weighting approach, which is used to weight stocks in an equity portfolio and explain how we use it in the context of this thesis.

Cheng et al. (2012) analyzed the common responses of prices and positions of all trader groups in the commodity futures markets to movements in the VIX index (a proxy for the risk appetite of traders). Their finding is that speculators (Commodity index traders and hedge funds) positions react negatively to the VIX during the recent financial crisis. [3] The resemblance to our paper is that we try to find an explanation for the change in the net long position of speculators as well, but focus not only on the financial crisis but on a more extended period.

In the inverse volatility strategy, the risk is measured with volatility, and assets are weighted in inverse proportion to their risk. Therefore get assets which have a lower volatility a higher weight in the portfolio. [19] In our research, we do not construct a portfolio, but since traders might apply the inverse volatility strategy, we research the change the effect of the change in the volatility as an explanatory variable (see chapter 3.5.1). Note that we calculate the volatility based on the returns and that the volatility for every period in time is smaller than one. The change of the inverse volatility is given in the following formula:

$$d(\frac{1}{\sigma_{t+1}}) = \frac{1}{\sigma_{t+1}} - \frac{1}{\sigma_t} \tag{10}$$

When the underlying volatility decreases from t to t+1, then the change of the inverse volatility takes a negative value. When the volatility increases the change in the inverse volatility takes a positive value.

3.4 Data Transformations

After calculating the signals and gathering the data, we still have to transform the trading signals as well as the raw data from the various reports. In a first subchapter, we show how we conclude from a trading signal to a signal that indicates a reallocation of the position. In the later subchapter, we explain how we calculate essential variables from the reports, which we can, later on, use as a dependent variable when we create a statistical model.

3.4.1 From Trading Signals to the Reallocation Signals

In chapter 3.2, the goal was to give an overview of how we calculated the trading signals. Both, the momentum as well as the carry calculations, resulted in a signal that measures the strength. Our objective is to measure the effect of a possible reallocation of the ideal position due to the change of the sign of the trading signal and conclude from that change to the change in the position of the traders. To do so, we defined a buy and a sell signal, whereas the buy signal equals 1 and the sell signal -1, regardless of the strength of the signal (see chapter 3.2). We do so by calculating the signum of the signal strength. By calculating the first difference of our binary signal, we get an indicator, that shows us that we change our position. Algebraically we transform the strength of any signal (s_t) as follows

$$dS_t \ = \ sgn(s_t) - sgn(s_{t-1}) \tag{11}$$

The new series dS_t now has three possible values. The first is zero; this is the case when the trading signal did not change. Second, it can be +2 when the signal changes from a sell signal to a buy signal (1 – (-1) = 2). The third, the signal has a value of -2, when the signal changes from a buy signal to a sell signal.

3.4.2 Transformation of the COT-Data

As a first measure, we define the net position, according to Moskowitz et al. (2012). The net measurement shows whether the aggregate of traders, in a particular futures market, is net long or short. Moskowitz et al. (2012) scale the net position by the total open interest, which is the total number of outstanding contracts in a specific market. Since we are interested in the change of the net position, we define Q as the net trading position, according to Kang et al. (2014). They differ in the calculation of Q, in their paper, they divide the difference of the net position from t to t+1 by the open interest at time t, but since the open interest is not fixed and can change, we define the net trading measurement as:

$$Q_{i,t} = \frac{long_{i,t} - short_{i,t}}{OI_{i,t-1}} - \frac{long_{i,t-1} - short_{i,t-1}}{OI_{i,t-1-1}} \tag{12}$$

Q can change from t to t+1, if either the net positions increases or decreases, due to an increase in long positions or a decrease in short positions, or if the open interest changes substantially. To evaluate where the change comes from, we further define a measurement for the long and short positions:

$$\Delta short_{i,t} = \frac{short_{i,t}}{OI_{i,t}} - \frac{short_{i,t-1}}{OI_{i,t-1}} \tag{13}$$

$$\Delta long_{i,t} = \frac{long_{i,t}}{OI_{i,t}} - \frac{long_{i,t-1}}{OI_{i,t-1}} \tag{14}$$

Using the formulas 13 and 14, we can analyze more precisely the effect of a reallocation of the positions, due to the change of the signal onto the delta long and short positions. Note that we further on also use the terms of delta net long position or change of the net long position for Q.

3.5 Statistical Framework

To analyze the effect of the reallocation of our portfolio onto the change of the positioning of the Traders classification, we use the estimation technique ordinary least square (OLS). The multiple regression is flexible and one of the most used analytical methods. It is a linear approach to modeling the relationship between two or more explanatory variables (independent variables) and the response variable (dependent variable) [20, p. 64]. The concept of this regression analysis is mainly applied in empirical economic and social research as well as in applied econometrics [21, p. 405].

In the regression model, we estimate the effect of the reallocation signals, the change in the risk appetite and volatility onto Q. We do this analysis for all the classifications from the CFTC which are regarded in this thesis.

3.5.1 Effect of Reallocation on the Change of the Net Trading Measure

We use a multiple regression model to estimate the impact of the reallocation of the traders' position, due to a change of the trading signal, onto the change of the net trading measure. The whole model consists of the reallocation signals and the first difference of the VIX as a proxy for the change of the risk appetite of financial traders, and the change of the inverse volatility.

The linear model looks as follows:

$$Q_{i,t} = \beta_0 + \beta_1 * dmom_{i,t} + \beta_2 * dcarry_{i,t} + \beta_3 * dVIX_t + \beta_4 * dinv\ vola_{i,t} + \epsilon_{i,t}, \quad i = 1, \dots, 33 \ and \ t = 0, \dots, n \tag{15}$$

$dmom_{i,t}$	is the change in the momentum signal or the so-called reallocation signal of the momentum strategy in the futures market i at time t.
$dcarry_{i,t}$	is the change in the carry signal or the so-called reallocation signal of the carry strategy in the futures market i at time t.
$dinv\ vola_{i,t}$	is the change of the inverse volatility from t to t+1
$dVIX_t$	is the change in the volatility index, which is a global variable for the change in the risk appetite; thus, it is the same variable for every futures market.
$\epsilon_{i,t}$	Is the stand normal distributed error with a mean of 0 and a standard deviation of 1, for the market i at time t.

We chose to use a multiple regression model because it is simple to implement and powerful tool when estimating the effect between explanatory and a dependent variable. From the literature, we found other modeling approaches, such as panel regression techniques. The problem with panel regression models is that it assumes that the number of explanatory variables grows to infinite, where the number of regarded points in time is fixed [22, p. 490]. That assumption is not met in our analysis since we consider up to 21 years with weekly data points and only up to four variables per futures market. Another technique that is often used is the Fama-Mac Beth regression. It was used to investigate whether the hedging pressure, momentum and term structure portfolios explain cross-sectional commodity futures returns, but since we are not interested in estimating the risk premiums, the method does not seem appropriate.

In our regression analysis, we have to analyze and modify the time series data before we estimate the regression. Firstly, time series with price data often contain a trend. If we took the raw data (with a trend), we would get spurious regression results, which would be invalid, because it violates the following assumption of linear regression models; that the mean of the residuals is stable over time of a linear regression model. In our analysis, we remove the trend by transforming the data and take the first difference as regressors. Secondly, we have to consider that there could be an autocorrelation within the residuals, which would violate the assumption that the residuals are independently distributed. To overcome this issue, we use heteroskedasticity- and autocorrelation- consistent (HAC) estimators of the variance-covariance matrix to get around this issue.

3.6 Data handling

In this chapter is written, how we transformed the data and calculated the necessary variables, as well as how we estimated the model. For the calculations, we used python primarily.

3.6.1 Data Control and Validation

An overview of the futures markets, which we research in this thesis is given in chapter 3.1. Since we calculate different trading signals, we have to download the futures prices in different ways.

To calculate returns and the momentum signals, we adjusted the commodity settings in the Bloomberg terminal, with the idea to use ratio rollover and active futures contract to have liquid prices across markets. Then we download the prices of the first generic futures price in which we entered the ticker and the appropriate suffix, “comdty” for commodities and the fixed income futures and “curncy” for the currency futures. To finally download the prices, we added “last_px” as an attribute.

To calculate the carry of the commodities; it was essential to have no lookahead bias and no adjusted rollover within the price. Since there are no reliable spot prices, we used nearest, second-nearest, and third-nearest to the expiration futures prices. We linearly interpolated approximative three-month maturity and later on scaled the factor to one-year maturities. For example, for the nearest to maturity contract, we downloaded the date of expiration and the price of the current future. We did not use generic futures contracts, but instead the underlying "real" futures data. First, we define for example the first to expiry futures as "XX1 R:00_0_N COMDTY", where XX stands for the ticker of the underlying futures market. Then we downloaded the expiry date with the attribute "CURRENT_CONTRACT_MONTH_YR" and the current price with "px_last". We did this as mentioned above for the nearest, second-nearest and third-nearest to expiration futures prices. An advantage of doing it that way is that we always know how many months between the two contracts are, a disadvantage is that generic futures are generally longer available and that the data is less smooth.

For the calculations of the carry in currency futures, we used forward points, for each currency pair. We downloaded the pips with the ticker "XXX12M CMPL Curncy" and calculated the forward premium or discount and, defined that if there is a premium, then we would go short and if there is a discount we would go short. To calculate the carry of the treasuries, we used the difference of the yield from the ICE Libor USD 3 Month and the US generic govt X-year yield, where X stands for the number of years which are equal to the treasuries.

After downloading the data, we first checked the data for inconsistencies by checking the downloaded data against the data in the Bloomberg terminal. The goal of this method was to find the wrongly handled data.

By estimating the statistical model, we had a problem with different periodicities, because the CFTC publishes the reports weekly, and we obtained daily data for the prices and the VIX index. We overcame this problem by calculating the mean over a rolling window of five days for the signal strength and then calculated the signum and the first difference, to get the signal for the reallocation. We applied the same procedure for the volatility and the VIX, with the difference, that we did not calculate the signum. This way, we still do not have a look ahead bias in the data and can estimate unbiased models. To merge the data, we used a left outer join, with two data frames. We created for each specific futures market two data frames, one that consists of the daily data (reallocation signals, and first difference of the inverse vola and the VIX Index) and one that contains the weekly data (position changes of the trader). After merging the data, we were able to calculate the regression model. Since we calculate up to 33 regressions per classifications, we automated the process of joining the data frames and the estimation of the models and wrote the important variables into a separate data frame.

3.6.2 Summary of the Data Set

The final dataset compromises 33 US futures contracts, whereas 22 are commodities, seven are currencies, and four are US fixed incomes futures.

Each futures contract consists of a daily return series, a carry and a momentum signal, as well as the first differences of the trading signal and the change of the inverse volatility. Furthermore, each commodity has a weekly change of position for the classifications of non-commercial traders and managed money. The financial futures (currency and fixed income) have, in addition to the change in the position of the non-commercial traders, also the classifications of asset managers/ institutional and levered funds. In addition to the price related data, we also added the change of the VIX as a global explanatory variable.

Further, we calculated for each market the measurement Q, as well as the delta long (Δlong) and the delta short position (Δshort) for the non-commercials. For the other classifications (managed money, asset managers/ institutional, and levered funds), the data set consists of the Q measurement. In addition to these variables, we have the first difference in the volatility index.

The time horizon of the statistical models we consider two different time horizons, the first for the non-commercial traders is from November 11, 1997, to February 26, 2019, with weekly data points, which results in 1111 data points. For the secondary analysis, where we analyze the effect on the subclassification, we regard a time horizon from June 20, 2006, to February 26, 2019, with weekly data points, which results in 662 observations.

4 Empirical Results

The empirical results contain two main chapters. In the first chapter, we are focusing on the analysis of the main variables, which we, later on, analyze in a regression model. The second chapter contains the results from the regression analysis, which we use to answer the research question.

4.1 First Analysis and Summary Statistics

We first analyze the returns and performance of the momentum, carry and long-only strategy and take a look at the distribution of the returns, with the ulterior motive that if the strategy performs well, we think the reallocation signal from that strategy should be able to explain the change of the net trading position of the traders (see chapter 4.1.1). Second, we analyze the open interest by the number of contracts of the different markets and analyze the history. Third, we focus on the analysis of the data provided by the CFTC. More specifically, we examine the open interest of all the considered futures (see chapter 4.1.3). In the next chapter 4.1.4, we compare the speculators change in the net trading measure Q, over the different markets, as well as the connection between the delta long, delta short as well as delta Q measurements that we have defined in the chapter 3.4.2. In the end, we are providing some statistics for the positions of the classifications managed money, asset managers/ institutions as well as levered funds.

4.1.1 Performance Return Comparison

In a first analysis, we compare the performance of the momentum, the carry, and the long-only strategy. To do so, we examine the excess cumulative returns, the volatility, and the Sharpe ratios. We calculated the returns by multiplying the signal lagged by one day with the discrete returns in the next period, where we calculated the discrete returns with the generic adjusted futures prices. The formula for the returns is:

$$r_{i,t} = \frac{F_{i,t}}{F_{i,t-1}} - 1 \qquad (16)$$

The goal is to see which trading strategy performs in which markets better, with the ulterior assumption that if a strategy works well in a market, that it has higher explanatory power for the change in the position of the traders.

In Table 1 below, the worst performing strategy is highlighted red and the best performing green. Note that the Sharpe ratio is the average return per unit of volatility. Thus if we as investors have two strategies with the same performance, we would take the strategy with a higher Sharpe ratio, because the higher it is, the more attractive is the risk-adjusted return.[23] For futures contracts, it is calculated as $SR_i = \frac{\bar{r_i}}{\sigma_i}$

Overall the momentum strategy can achieve the highest mean cumulative return of 53%, followed by the carry strategy of 49%. The worst performing overall is the long-only strategy, with a mean of 33%. Looking at the different markets and sectors, the order of best-performing strategy does not change when we look at all commodities. For the currency futures market, it is the carry strategy that outperforms the momentum and long-only strategy, where the long-only strategy is not able to beat the momentum strategy. By looking only at the performance in the fixed income futures market, the order changes significantly; the long-only strategy outperforms the others, with a mean of (85%), followed by the carry (55%) and the momentum (64%).

The Time interval of this analysis is from November 11, 1997, to February 26, 2019. Except for Gasoline (XB1) the start date the March 2, 2006, for Euro FX (EC1) it is the May 19, 1999, and for the New Zealand Dollar (NV1) it is June 18, 2002.

Table 1: Performance comparison of momentum-, carry-, and long-only strategy

Summary statistics of the performance of the strategies (momentum, carry, and long-only) in the regarded futures market. This table provides an overview of the excess cumulative return (c. excess return) per strategy (momentum, carry and long-only) and specific market (Ticker) for the considered years (#year). Further, we provide the standard deviation (vola), and the Sharpe ratio (SR)

Performance Comparison

	Ticker	#years	Momentum Strategy			Carry Strategy			long-only Strategy		
			cumulative return	vola	SR	cumulative return	vola	SR	cumulative return	vola	SR
Energy	CL1	21.3	368%	28%	0.27	243%	36%	0.21	-6%	37%	-0.01
	XB1	12.2	51%	26%	0.13	58%	35%	0.15	127%	34%	0.27
	NG1	21.3	-40%	40%	-0.06	-93%	51%	-0.3	-99%	51%	-0.54
	HO1	21.3	615%	25%	0.38	100%	34%	0.01	205%	34%	0.21
Metals	GC1	21.3	2%	13%	0.01	-53%	17%	-0.28	153%	17%	0.36
	SI1	21.3	-23%	21%	-0.06	-85%	29%	-0.39	84%	29%	0.14
	PL1	21.3	103%	18%	0.19	99%	23%	0.19	143%	23%	0.24
	HG1	21.3	154%	20%	0.23	4%	27%	0.01	113%	27%	0.18
Agricultural	W1	21.3	-40%	21%	-0.11	238%	29%	0.27	-95%	29%	-0.6
	KW1	21.3	102%	20%	0.17	745%	27%	0.52	-87%	27%	-0.46
	S1	21.3	16%	17%	0.04	183%	23%	0.3	69%	23%	0.15
	C1	21.3	5%	18%	0.01	26%	26%	0.06	-86%	26%	-0.47
	BO1	21.3	43%	17%	0.1	-53%	23%	-0.21	-58%	23%	-0.24
	SM1	21.3	4%	18%	0.01	-58%	26%	-0.22	551%	26%	0.5
	CT1	21.3	156%	19%	0.23	62%	26%	0.12	-82%	26%	-0.4
	KC1	21.3	-54%	24%	-0.15	44%	34%	0.07	-95%	34%	-0.54
	SB1	21.3	123%	24%	0.16	3%	32%	0.01	-62%	32%	-0.19
	JO1	21.3	-19%	22%	-0.05	-93%	31%	-0.54	-44%	31%	-0.13
	CC1	21.3	-69%	21%	-0.26	-41%	29%	-0.12	-50%	29%	-0.16
Live stock	FC1	21.3	30%	11%	0.12	-23%	15%	-0.11	23%	15%	0.09
	LH1	21.3	-9%	19%	-0.02	-75%	25%	-0.34	-95%	25%	-0.71
	LC1	21.3	27%	11%	0.1	-58%	15%	-0.36	-27%	15%	-0.13
Currencies	BP1	21.3	6%	7%	0.04	-15%	9%	-0.11	-11%	9%	-0.08
	EC1	19.8	55%	7%	0.31	75%	10%	0.4	-10%	10%	-0.07
	CD1	21.3	13%	6%	0.09	-41%	9%	-0.39	8%	9%	0.06
	AD1	21.3	55%	10%	0.22	79%	13%	0.29	55%	13%	0.22
	JY1	21.3	24%	8%	0.13	-31%	11%	-0.22	-31%	11%	-0.22
	NV1	16.7	40%	10%	0.21	156%	13%	0.59	170%	13%	0.63
	SF1	21.3	-41%	9%	-0.28	-5%	12%	-0.02	-5%	12%	-0.03
Fixed Income	TU1	21.3	19%	1%	0.64	4%	2%	0.16	27%	2%	0.9
	FV1	21.3	28%	3%	0.39	23%	4%	0.33	67%	4%	0.83
	TY1	21.3	26%	4%	0.24	55%	6%	0.47	108%	6%	0.79
	US1	21.3	-9%	7%	-0.07	136%	10%	0.58	136%	10%	0.58

The carry strategy works well in the agricultural- and bad in the sector metals sector. The cumulative returns in the long-only strategy also show the increase or decrease of the price in any given futures market over the investigated period. For example, we see that the price of crude oil futures (CL1) approximately reduced by six percent from November 26, 1997, to February 26, 2019, while the futures price for heating oil (HO1) more than doubled. We can see that the returns overall vary a lot within the sectors and markets.

Furthermore, we highlight that in the markets of JO1 and partly the FC1, neither momentum nor carry performance returns generated a positive mean return, this might be due to the illiquidity of these futures markets. Reasons for the illiquidity are discussed in chapter 4.1.3, Figure 2.[14]

4.1.2 Distribution of the Returns

In the next step, we analyze the distribution of the returns, with the annualized excess mean return, the kurtosis and the skewness of the distribution, the results are in Table 9 in the Appendix (chapter 7.2). The calculation of the annualized mean excess return is:

$$\left(\frac{cumulative\ performance_{T}}{100}\right)^{\frac{1}{T}} - 1\ , \tag{17}$$

where T is the number of regarded years, and the numerator is the cumulative performance at time T. Since we already analyzed the performance of the different approaches, we focus here on the distribution of the returns.

The Kurtosis measures if the distribution is more or less peaked than a normal distribution. A normal distribution has a kurtosis value of three. If the value is higher, it means that the return distribution is relatively peaked in comparison to the normal distribution and that the distribution has fat tails. If the value is smaller than three, it means that the distribution is relatively flat and light-tailed, compared to the normal distribution [24]. By examining the different strategies, we found that especially with the momentum strategy, the distributions of all future market have heavy tails. When we look at the carry strategy, we see that the distributions are quite similar to the long-only strategy, where the kurtosis is smaller than three in the agricultural- and partly in the energy commodities and fixed income futures markets.

The skewness measures the degree of asymmetry, where negative values show that the distribution with a tail extending to more negative values, a positive value indicates therefore that the distribution has a tail extending to more positive values [24]. We found that the skewness of the carry and momentum strategy is quite similar to the exception in the metal commodities, where the returns of the carry strategy are positively and in the momentum strategy negatively skewed. By looking at the skewness of the long-only strategy in Table 9, we found that the distributions are generally less skewed with a more positive value.

4.1.3 The Open Interest Over Time

In this subchapter, we are going to take a more in-depth look into the open interest by the number of contracts, which will be used to scale the trader's positions, as written in chapter 3.4.2.

What is the connection between liquidity and open interest? A liquid investment is something that can be bought and sold with ease. The open interest can, therefore, be used as an indicator for the liquidity of a futures market, because it is the total amount of outstanding futures contracts entered and not yet offset.

In the first graph (Figure 1), we plot the open interest of the 16 futures, that had the hugest open interest at the end of the research horizon (February 26, 2019). The open interest which is plotted for every futures market is more precisely the rolling mean of the open interest with a window of 52 weeks. The reasoning is that we wanted to show a smoother graph and mitigate seasonality. The legend is placed in the top left corner of the figure, which gives an overview of which futures are within those sixteen. By analysing the legend, where the futures are ranked by open interest by the end of the period, that the US T-Notes with five and two years (FV1, TY1 – size: 4.2 and 3.9 Mio) have the highest open interest followed by crude oil (CL1 - size: 2.6 Mio), Corn (C1 -size: 1.8 Mio). The “lowest” open interest has heating oil (HO1) with an open interest of 400’000. We can see in the legend, that it contains futures from every sector or market, except for the livestock futures.

Furthermore, we can see that there is a positive trend, starting in the year of 2003 till the middle of 2008. This increase in the open interest is a result of the massive investment inflows from commodity futures indices, where the inflow in this time interval increased from $13 billion to about $ 260 billion.[9]

The collapse after 2008 is a consequence of the financial crisis. Looking at the graph, we can see that in the year 2010, the futures markets recovered, and open interest increased again but needed around five years to climb to the level of 2008.

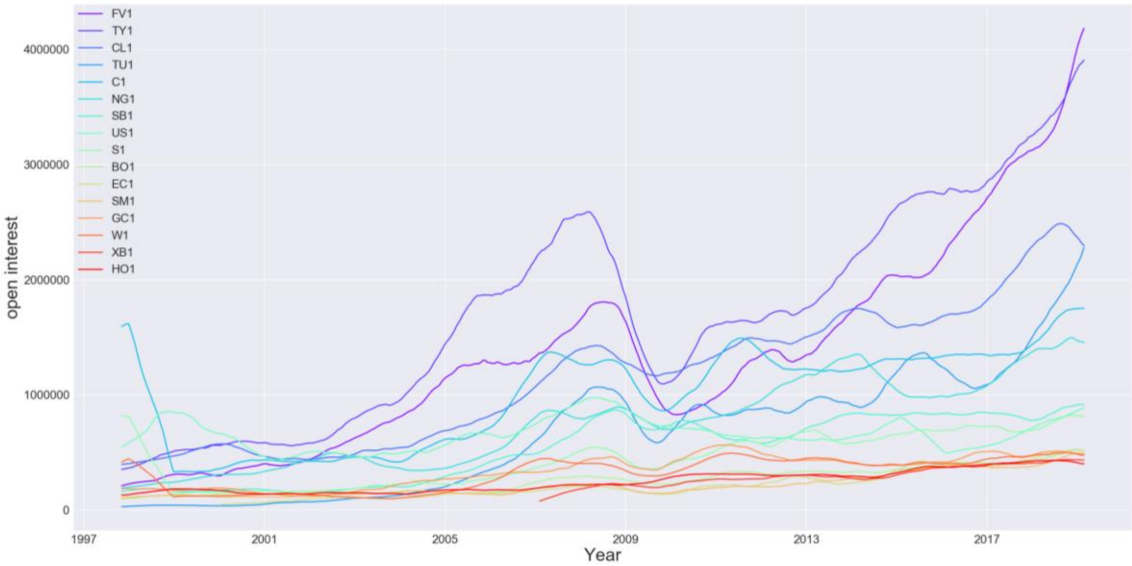

Figure 1: Open interest of the 16 futures, that have the biggest open interest

In the next step, we look at the futures which have a lower total interest. They are visualized in Figure 2. The graph is organized the same way as Figure 1. By analyzing the chart, we can see a similar picture as before. One difference we can see is that it seems that the mentioned inflow of investments above, has taken place later (around 2005), but the increase is significantly steeper. Moreover, we can see that not all of the markets were affected the same from the recent financial crisis. Looking at the individuals, we see a sharp decrease at the beginning of the period, which is from wheat #2, hard winter (KW1), a similar reduction can further be seen in Figure 1 from wheat (W1). It just seems to be stronger in Figure 2 because the scales on the y-axis are different. The lowest open interest have Frozen Orange Juice (JO1), feeder cattle (FC1), and New Zealand Dollars (NV1), which is as mentioned above an indicator for illiquidity.

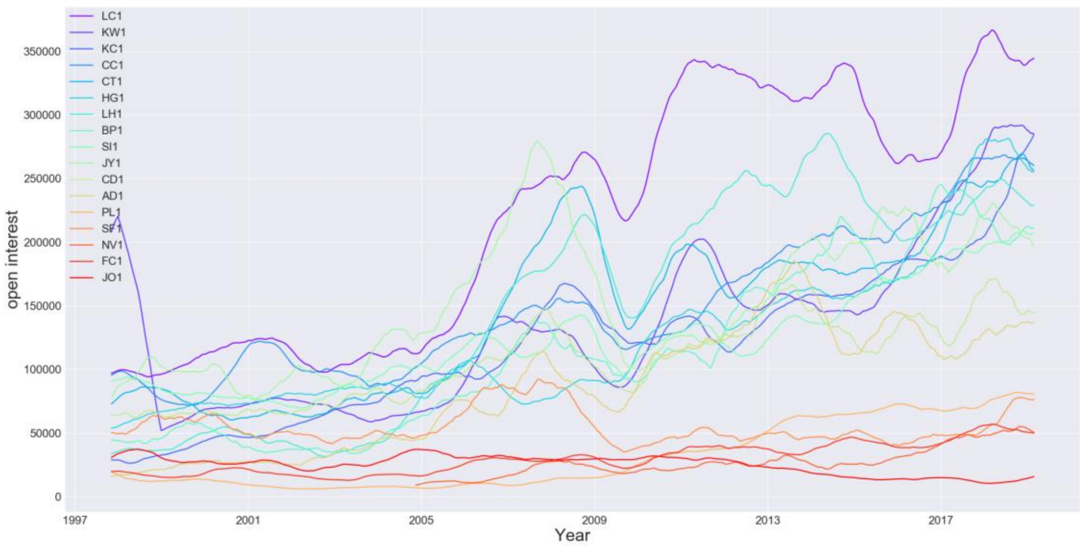

Figure 2: Open interest of the 17 futures, that have a lower open interest

As a result of this analysis, we take away, that we can see the inflow starting in 2003, as well as the crisis. Further, we can see a positive trend across all futures markets, which is an evidence to consider not only the changes in the long/ short/net positions but as well the change in the open interest, as formulated in the chapter 3.4.2.

4.1.4 Analysis of the Traders' Position

This chapter consists of two studies, where we first focus on the change of the net trading measurement across the Markets, we do so by calculating the Pearson correlation of the change in the net trading position (Q) for every futures pair and show the results in a heatmap. In a second step, we focus on the connection between the delta long, delta short, and Q.

The goal of the first analysis is to find out, if futures which belong to the same sector or market, behave the same way. In the following Figure 3, we organized they and the x- and the y-axis the following way: the first four tickers are energy-, then four metals, the six grain-, then the five soft commodities. Note that grain and softs are subsectors of the agricultural commodity sector. So after the agricultural futures come three live stock-, followed by the seven currency- and the four fixed income futures. The meaning of the color can be seen in the right bar next to the heatmap, where red tones state that there is a positive correlation and blue a negative one.

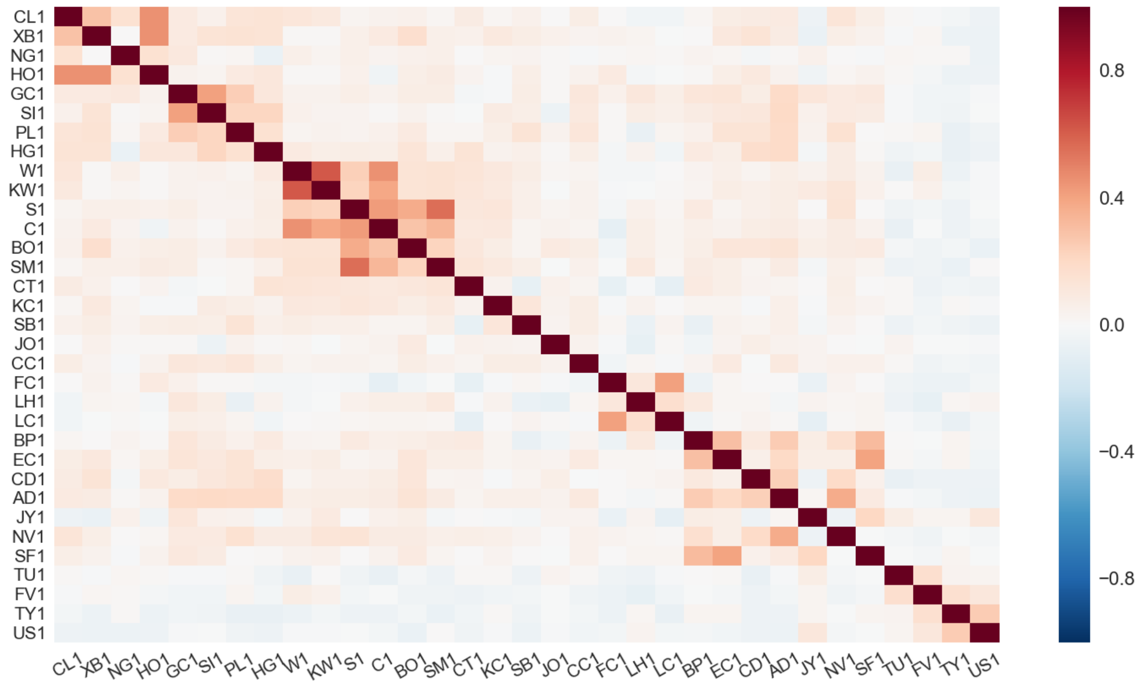

Figure 3: Heatmap of the correlation of Q, across all regarded futures

By going along the diagonal axis we can see that most of the described sectors form a box, of more reddish colored fields, this means that within the sectors, there is a higher correlation in the change of the net trading position. This means that if Q of an individual futures market increases or decreases, the futures in the same sector are moving in the same direction. Only in the sector of the soft commodities (CT1 to CC1) is this phenomenon not observable.

Focusing on the bottom of the graph, we can see that the US treasuries futures have a low negative relationship with almost all of the other futures. Additionally, we can see that there is also a stronger correlation between futures of currencies and metals and a rather weak connection between the currencies and the live stocks. The most substantial relationship overall has two wheat commodities (W1 and KW1).

In the next step, we try to figure a connection between the *Δshort*, *Δlong*, and *Q* measurements. The calculation of these measurements is stated in chapter 3.4.2.

To find a connection between these different measurements, we first calculate the Pearson correlation for every futures contract between those three variables and present them in a hierarchically-clustered heatmap with dendrograms. The clustering algorithm reorders the futures contracts in a way, where it searches another futures contract that is the most similar to the first futures contract, in our case, the one that is the most identical to XB1. The dendrograms indicate both the similarity and the order the clusters were formed. On the x-scale of Figure 4, is *Q* for the change in the net trading position, *dlong* stays for Δlong position and *dshort* for Δshort positions. The y-axis is again the tickers for the futures. The color of the squares is an indicator of the correlation, where dark blue stays for a strong negative correlation and dark red for strong positive red for a positive relationship.

When we look at the columns Figure 4, we see that across all futures contracts, the result is homogenous. Further, we see that the correlation between the net long position and the dlong position is highly positive (column 1 – from the left), and that the association of the change in the net long position and the delta short position is highly negative (column 3 – from the left).

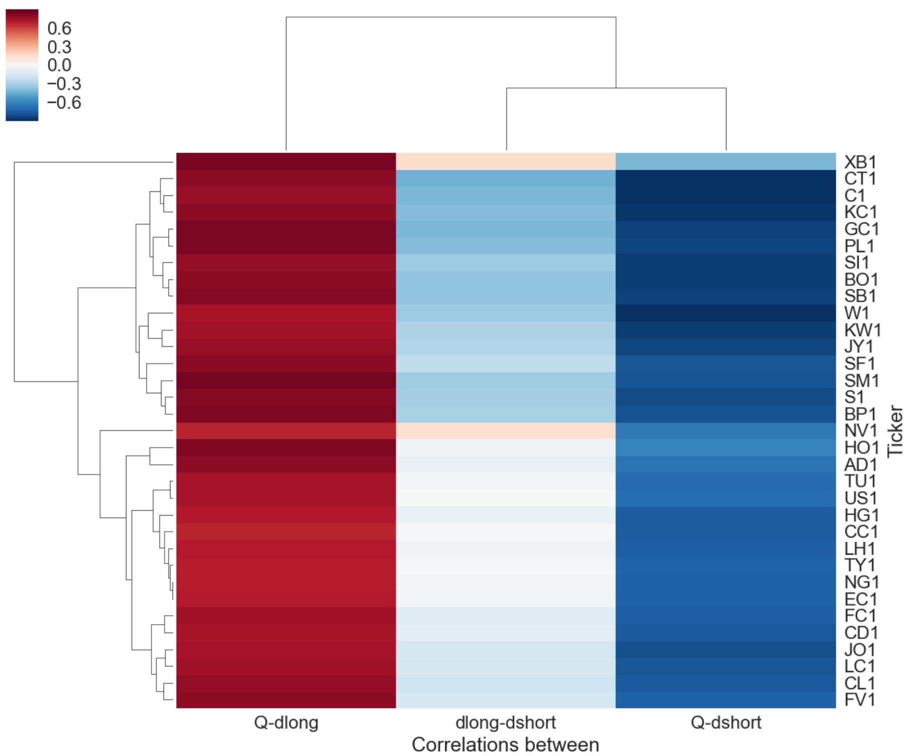

Figure 4: Cluster map of the different positions form the legacy report

The dendrograms show us that the second and the third column build a cluster, and the first column itself is a cluster. This can be interpreted that the correlation between Q and d*short* is similar to the relationship between d*long* and d*short* positions.

Algebraically we analyzed the following correlations and came to the overall conclusion:

$$cor(\Delta short, \Delta long) \rightarrow effect\ weak\ negative$$

$$cor(\Delta net\ long, \Delta long) \rightarrow effect\ strong\ positive$$

$$cor(\Delta net\ long, \Delta short) \rightarrow effect\ strong\ negative$$

These findings lead us to the conclusion that when the change in the net trading position decreases its due to an increase in the short positions and a simultaneous decrease in the long positions. When Q increases its contributed by a rise in the long positions and a fall in the short positions, thus we can analyze different effects on solely the measurement Q. Now that we understand the link between the different measurements, we take the assumption that this behavior does not change across the classifications of the CFTC.

4.1.4.1 Summary Statistics of the Classifications

In this subchapter, we take a more in-depth look into the two classifications, from the TFF report and the classification of managed money from the DCOT report.

The classifications from the TFF report, namely "asset managers/ institutional", and "levered funds" are regarded for the period from June 20, 2006, to February 26, 2019.

The mean of the change in the net trading position of the traders is over the whole period is almost zero for both classifications. However, by comparing the two classifications, we can see a significant difference. The classification of asset managers/institution is the mean overall positive, whereas, in the other classification, it is more often negative. The column "mean" in the table above shows us the average change in the position, but not the average position they took. To see the average position, we have to look at the net position only, which is the long – short position. We found that the classification of asset managers, institutional is average short in the following markets: BP1, AD1, and SF1, whereas the classification of levered funds was on average short in the markets of EC1, CD1, JY1, NV1, FV1, TY1, and US1.

Table 2: Summary statistic of the positions in the TFF-report

Summary statistics of the change in the net trading position of the two classifications Asset Managers/Institutional and Levered Funds. The summary statistics consists of the arithmetic mean (mean), standard deviation (stdv), and the 5% and 95% quantile values, for both classifications and every financial futures contract, that is regarded.

		TFF							
		Asset Managers and Institutional				Levered Funds			
	Ticker	Mean	Stdv	5%	95%	Mean	Stdv	5%	95%
Currencies	BP1	0.006	0.090	-0.153	0.148	0.004	0.104	-0.169	0.146
	EC1	0.006	0.109	-0.124	0.186	0.001	0.088	-0.144	0.138
	CD1	0.001	0.053	-0.077	0.094	0.000	0.098	-0.176	0.121
	AD1	0.000	0.105	-0.132	0.136	0.004	0.131	-0.208	0.217
	JY1	0.001	0.043	-0.069	0.056	-0.001	0.075	-0.109	0.106
	NV1	0.003	0.166	-0.257	0.221	-0.001	0.243	-0.310	0.369
	SF1	-0.004	0.058	-0.066	0.065	0.001	0.115	-0.128	0.143
Fixed Income	TU1	0.008	0.072	-0.092	0.126	-0.011	0.082	-0.175	0.099
	FV1	0.008	0.087	-0.085	0.132	-0.007	0.059	-0.093	0.064
	TY1	0.005	0.048	-0.055	0.088	-0.005	0.051	-0.094	0.073
	US1	0.004	0.021	-0.024	0.040	-0.003	0.020	-0.038	0.018

We see that levered funds in the mean over the whole period were net short in the futures of fixed income, whereas asset managers/ institutional are net long on those futures contracts, this could come from the fact that insurance companies, which are more risk averse, are also in this classification. When we take a look at the quantile values, we can see that the absolute values of levered funds are higher, this means that the distribution of these funds probably has fat tails and a slightly flatter distribution. This could be an indicator, that levered funds as a class are more homogenous than the asset managers since the values have higher variability.

We compare the money managers with the non-commercial traders since we are not researching another commodity classification. The results (Table 10) are in Appendix (chapter 7.3). The structure of the table is the same as in Table 2. We compare arithmetic mean, standard deviation, and the 5% and 95% quantiles. We get a similar conclusion to the one above, where the non-commercials take the place of the asset managers/institutional, and the class of managed money takes the position of the levered funds. In terms of the threshold of the percentile values are consistently absolute more significant for managed money, which can be seen as an indicator, that this class is more homogenous than the class of non-commercial traders. Moreover, we can see that the mean over time for non-commercials is approximately zero with no exceptions further is the standard deviation smaller than for the class of managed money.

4.2 Impact of Reallocation in the Futures Markets

In this chapter, we are analyzing the statistical model, which we described in chapter 3.5. We first apply the model on the commodity market, where we are comparing the classifications of non-commercials and managed money. In the next analysis, we use the model to estimate the effect on the position of the TFF, as well as the classification of the non-commercial traders from the legacy report.

The results of the regressions are noted in different tables, where we on purpose left out the estimation for the intercept (β_0), because it was not significant on the ten percent level for any of the considered futures contracts.

4.2.1 Impact of Reallocation in Commodity Futures Markets

In this chapter, we are analyzing the results of the regressions on the change in the net trading measure Q, in commodity futures markets. We examine the effects on the classification of non-commercial traders and money managers and provide a comparison of those two classifications in the end.

Non-Commercial Traders

In the following table (.

Table 3), we summarized the output from our regression analysis, where we estimated the relationship between the reallocation signals from carry and momentum, the change in the risk appetite and the change in the inverse volatility onto Q.

In the column of the “dmom”, we can see that the effect is positive and significant on at least the 5% significance level overall commodity futures markets. Therefore we conclude that the reallocation signal from the momentum strategy has a significant impact on the change in the traders positioning. Since the estimated coefficient is positive for all commodity futures, we found that a change from a sell to a buy signal has a positive effect. Note, if the signal changes from a buy to a sell signal, the value is minus two, if it turns from a sell signal into a buy signal the value is plus two. Therefore is the effect on the net long position plus-minus two times the coefficient. The highest impact can be observed in the sector of metals, where the effect is up to 5% (±2*0.025) change in Q.

In the next column “dcarry”, is the estimation of the coefficient, which measures the effect of the reallocation signal from the carry strategy. We can see that the estimated coefficient can be positive or negative, but the effect occurring from the change in the carry trading signal is smaller than the effect from the momentum signal. We also see that the estimated coefficients are not all significant. If a coefficient is not significant, it means that the null hypothesis; that the coefficient is equal to zero cannot be rejected. Moreover, we found that the significant coefficients are all positive except for Kansas wheat (KW1). For the positive coefficients, we found the same interpretation, as for the momentum coefficients. When the coefficient is negative, it means that it has the inverse effect, which means that the change from a sell to buy signal has a negative effect on Q. Reason for the result for KC1 could be that we only have 15 changes in the signal over the whole period of investigation. The highest significant impact of the reallocation signal from carry can be found for sugar (SB1), where the impact is 2.8% ((±2*0.014)

In this regression model, we researched the time interval from November 11, 1997, to February 26, 2019, except for Gasoline (XB1) is the start date March 7, 2007. The exception for XB1 is because the data has not been published further into the past by the CFTC.

Table 3: OLS estimation of non-commercials in commodity markets

Summary overview of the estimated betas for the momentum and carry reallocation signal (dmom, dcarry); the first difference of the VIX (dvix) and the inverse volatility (inv vola). In addition to the coefficient, we provide the p-values, as well as the coefficient of determination (R^2). To show the significance of the estimated betas, we use the following notations: '.' , '*', '**', '***' stand for the significance of the coefficient on the 10%, 5%, 2.5% and 1% level.

Non-Commercials - OLS Commodities

	Ticker	Coef. dmom	p-value mom	Coef. dcarry	p-value carry	Coef. inv vola	p-value inv vola	Coef. dvix	p-value dvix	R^2
Energy	CL1	0.003	0.05 *	-0.001	0.82	0.002	0.08 .	-0.002	0.09 .	0.009
	XB1'	0.005	0.05 *	0.004	0.07 *	0.002	0.09 .	-0.004	0.01 **	0.026
	NG1	0.011	0.00 ***	0.001	0.62	-0.001	0.25	0.001	0.10	0.020
	HO1	0.009	0.00 ***	0.003	0.24	0.002	0.02 **	-0.004	0.00 ***	0.033
Metals	GC1	0.025	0.00 ***	0.002	0.75	-0.001	0.55	0.000	0.98	0.027
	SI1	0.023	0.00 ***	0.002	0.48	-0.002	0.33	-0.003	0.11 **	0.025
	PL1	0.022	0.00 ***	0.003	0.27	0.004	0.05 .	-0.005	0.09 **	0.016
	HG1	0.033	0.00 ***	0.002	0.63	4E-04	0.79	-0.005	0.03 *	0.052
Agricultural	W1	0.014	0.00 ***	0.003	0.15	-0.006	0.00 ***	0.001	0.87	0.029
	KW1	0.022	0.00 ***	-0.005	0.00 ***	-0.005	0.02 **	-0.001	0.53	0.049
	S1	0.01	0.00 ***	-0.003	0.43	-0.002	0.07 .	-0.003	0.05 *	0.015
	C1	0.016	0.00 ***	0.003	0.05 .	-0.004	0.00 ***	0.000	0.70	0.038
	BO1	0.013	0.00 ***	0.011	0.04 *	-0.005	0.00 ***	-0.004	0.00 ***	0.029
	SM1	0.017	0.00 ***	0.006	0.08 .	-0.005	0.00 ***	-0.002	0.15 .	0.041
	CT1	0.016	0.00 ***	0.005	0.07 .	-5E-04	0.85	-0.003	0.07 ***	0.011
	KC1	0.021	0.00 ***	0.008	0.18	0.001	0.56	-0.004	0.09 .	0.014
	SB1	0.008	0.01 **	0.014	0.01 **	-0.005	0.02 **	0.001	0.66	0.024
	JO1	0.023	0.00 ***	-0.005	0.24	0.002	0.34	0.000	0.88	0.028
	CC1	0.015	0.00 ***	0.008	0.00 ***	0.002	0.02 **	-0.001	0.28 .	0.036
Live stock	FC1	0.021	0.00 ***	0.002	0.55	0.001	0.61	-0.003	0.08 .	0.009
	LH1	0.01	0.00 ***	-0.004	0.13	-2E-04	0.77	0.001	0.21	0.007
	LC1	0.007	0.01 **	0.002	0.41	-1E-04	0.71	-0.001	0.17	0.009

In the column "inv vola", is the estimation of the coefficient, which measures the effect of the change in the inverse volatility onto Q of non-commercial traders, as well as the p-values. By looking at the coefficients, we can see that the effect is minimal. However, we can see that the model estimates positive and negative coefficients. Since we look at the change in the inverse volatility, we have a positive value if the volatility increases and a negative one if the volatility decreases (see chapter 3.3). If the coefficient is positive, it means that an increase in the volatility has a positive effect on the change in the net long position. If the coefficient is negative, we conclude that an increase in the underlying volatility has a negative effect on the measurement Q.

By looking at the effect of the change in the risk appetite (column “dvix”) we also found positive and negative values as well, but all the significant values are negative, which aligns with the observation of Cheng et al. (2012). When we look at the coefficient of determination (R^2) we see that it is fairly low over all commodity futrues market. The coefficient of determination shows us how much of the variability of the dependent variable can be explained with the explanatory variables. Thus the rule is the higher, the better.

Managed Money

In the following table (Table 4), are the results of our estimation of the regression model on the change of the net trading measure for the classification of managed money. By looking at the first column “dmom”, we see that the estimations for the coefficients are all positive except for platinum (PL1), where the estimated factor is minimal and not significant. We also see that the coefficient of (KW1) is not significant on the ten percent significant level. The highest impact on a change in the momentum trading signal can be observed in the high-grade copper (HG1) futures market, where a change in the signal leads to a change in the net long position of plus-minus 14.4%.

Moving on to the reallocation signal from the carry-strategy, we found the estimations that are significant on any level are positive or negative. Moreover, we see that especially in the subsector grains, the estimations are significant. The gap in the row of KC1 is due to the singularity of the time series, meaning that during the period that was investigated, no change in the signal was observed.

In the third column, we estimated the beta for the change in the inverse volatility. We found that most of the significant values are negative, except for cocoa (CC1), which is positive. Moreover, we found that this variable is not able to explain the change in the net trading position over whole sectors and markets, but works fine for some agricultural commodity futures contracts.

The estimations for the change in the VIX index (column “dvix”) are overall negative which is consistent findings from Cheng et al. Further we see that especially in the metals commodity futures contracts the results are significant.

The time interval for the regressions is from June 20, 2006, to February 26, 2019, except for XB1 is the start date March 7, 2007.

Table 4: OLS estimation of money managers in commodity markets

Summary overview of the estimated betas for the momentum and carry reallocation signal (dmom, dcarry); the first difference of the VIX (dvix) and the inverse volatility (inv vola). In addition to the coefficient, we provide the p-values, as well as the coefficient of determination (R^2). To show the significance of the estimated betas, we use the following notations: '.' , '*', '**', '***' stand for the significance of the coefficient on the 10%, 5%, 2.5% and 1% level.

OLS Commodities - Managed Money

	Ticker	Coef. dmom	p-value mom		Coef. dcarry	p-value carry		Coef. Inv Vola	p-value inv vola		Coef. dvix	p-value vix		R^2
Energy	CL1	0.015	0.00	*	-0.002	0.85		-3E-04	0.64		-0.003	0.09	.	0.023
	XB1	0.032	0.00	*	0.020	0.01	**	0.003	0.11		-0.005	0.73		0.027
	NG1	0.033	0.00	***	0.007	0.12		-0.003	0.03	*	0.001	0.52		0.026
	HO1	0.019	0.00	***	0.005	0.32		0.002	0.06	.	-0.010	0.00	***	0.056
Metals	GC1	0.043	0.00	***	-0.013	0.20		-0.001	0.36		-0.005	0.39		0.037
	SI1	0.04	0.00	***	0.000	0.99		-0.001	0.55		-0.010	0.01	**	0.045
	PL1	-0.001	0.99		0.012	0.68		0.000	0.83		-0.056	0.02	**	0.013
	HG1	0.072	0.00	***	0.001	0.91		0.001	0.64		-0.010	0.04	*	0.063
Agricultural	W1	0.040	0.01	**	-0.023	0.00	***	-0.008	0.00	***	-0.003	0.41		0.066
	KW1	0.015	0.17		-0.006	0.09	***	-0.006	0.00	***	-0.003	0.17		0.036
	S1	0.037	0.00	***	-0.019	0.07	*	-0.002	0.16		-0.008	0.07	*	0.022
	C1	0.018	0.00	***	-0.013	0.12		-0.001	0.59		0.001	0.72		0.013
	BO1	0.033	0.00	***	0.036	0.00	***	-0.004	0.02	**	-0.010	0.00	***	0.043
	SM1	0.043	0.00	***	-0.002	0.81		-0.001	0.25		-0.004	0.09	.	0.043
	CT1	0.029	0.00	***	0.030	0.00	***	-0.002	0.33		-0.012	0.00	***	0.032
	KC1	0.022	0.00	***				-0.004	0.14		-0.003	0.22		0.022
	SB1	0.022	0.05	.	0.006	0.59		-0.004	0.00	***	-0.005	0.13		0.019
	JO1	0.014	0.00	***	-0.001	0.67		0.004	0.28		-0.005	0.21		0.021
	CC1	0.02	0.00	***	0.016	0.05	.	0.004	0.00	***	-0.003	0.17	.	0.030
Live stock	FC1	0.023	0.07	.	-0.005	0.33		0.001	0.17		-0.004	0.26		0.015
	LH1	0.021	0.05	.	0.005	0.60		-0.003	0.02	**	-0.002	0.74		0.015
	LC1	0.022	0.00	***	0.006	0.20		0.001	0.17		-0.003	0.22		0.018

Comparison

When we compare the regression results of the two classifications, we have to keep in mind that the time interval is not the same. We found that the effect of the reallocation signal of momentum has a higher impact on the traders that are classified in the class of managed money. Since the average beta for managed money is 2.7%, while it is 1.6% for non-commercial traders.

The comparison for the estimations of the reallocation signal from the carry strategy is difficult because the estimations sign partly changes for the estimations futures market in the different classifications. Overall, we found that the absolute effect is higher in the classifications of managed money. This can also be seen in the commodity futures of W1, KW1, and CC1, where the sign does not change.

When we compare the estimations of the change in the inverse volatility, we see that in the first regression analysis, more results are significant than in the second one, this could be because we have more observations, but we still found that the estimations are quite similar.

By looking at the change in the VIX index, we found that our estimations align with the findings of Cheng et al. (2012), that the increase in the volatility index has a negative impact on Q. In the comparison of the coefficient of determination, we found that in the estimations for the classification of money managers, the r-squared is slightly higher, and can, therefore, explain slightly more of the variability in the dependent variable.

4.2.2 Impact of Reallocation in Financial Futures Markets

In this chapter, we analyze the effects of the reallocation signals on Q and focus on financial futures. We examine the effects on the classification of non-commercial traders, levered funds, and asset managers/ institutional. We compare the results of the non-commercial financial futures with the same classifications for commodities and compare the results of the classifications from the TTF against each other.

Non-Commercial Traders

The summarized results are in Table 5; the table consists of the estimations for the variables with associated p-values. Also, we provide the coefficient of determination. The research period for this analysis is from November 11, 1997, to February 26, 2019.
Except for Euro FX (EC1) is the start date the 19th May 1999 and for the New Zealand Dollar (NV1) it is the 18th June 2002.

We found that the reallocation signal from the momentum strategy provides a significant positive effect in the currency futures market, which is consistent with the findings in the commodity futures market. In the market of fixed income are none of the estimated coefficient significant.

The estimation of the reallocation signal from the carry strategy is relatively small overall financial futures and only the estimations for Swiss Franc (SF1), and Australian Dollar (AD1) are significant, where the coefficient for AD1 is positive, and SF1 is negative. For NV1, we could not use the reallocation signal from carry as an explanatory variable because it was zero over the whole period we researched.

The estimated betas for the change in the inverse volatility are not significant for all fixed income futures. In the currency futures are four estimations significant on at least the ten percent level and four are not significant at all. The values of the significant estimations are mostly positive, which means that an increase in the volatility has a positive effect on Q. The estimations for the change in VIX index is significant for most currency futures, where the beta is negative except for NV1 and SF1. In the fixed income futures is the effect only significant on US T-Notes, 2-Year (TU1) and it is also positive. Overall are the estimated coefficients for the change in the VIX higher than they are in the commodity market.

The coefficient of determination is for all estimations fairly small, and we found that the values are smaller than the ones in the commodity markets. This means that we can explain even less of the variability in the change in the net trading measure.

Table 5: OLS estimation of non-commercials in financial futures markets

Summary overview of the estimated betas and p-values of the momentum and carry reallocation signal (dmom, dcarry); the first difference of the VIX (dvix) and the inverse volatility, where the dependent variable is Q from the non-commercial traders in financial futures In addition to the coefficient, and p-values, we provide as well the coefficient of determination (R^2). The time interval for the regressions is from the To show the significance of the estimated betas. We use the following notations: '.' , '*', '**', '***' stand for the significance of the coefficient on the 10%, 5%, 2.5% and 1% level.

OLS financial futures – Non-commercial traders

	Ticker	coef dmom	p-value mom		Coef. dcarry	p-value carry		coef inv vola	p-value inv vola		coef dvix	p-value vix		R^2
Currencies	BP1	0.033	0.03	*	-0.002	0.29		-0.024	0.17		0.006	0.11		0.01
	EC1	0.032	0.01	**	0.001	0.41		-0.01	0.26		-0.002	0.40		0.02
	CD1	0.038	0.00	***	3E-04	0.79		0.002	0.92		-0.015	0.00	***	0.06
	AD1	0.036	0.08	.	0.006	0.00	***	0.04	0.09	.	-0.019	0.00	***	0.04
	JY1	0.045	0.00	***	-0.001	0.64		0.001	0.00	***	-0.01	0.03	*	0.04
	NV1	0.032	0.03	*				0.003	0.09	.	0.01	0.00	***	0.03
	SF1	0.025	0.02	**	-0.004	0.02	**	-0.015	0.00	***	0.012	0.04	*	0.06
Fixed Income	TU1	0.002	0.70		1E-05	0.73		0.005	0.16		0.003	0.03	*	0.01
	FV1	-0.001	0.48		2E-05	0.87		-0.008	0.29		0.002	0.21		0.01
	TY1	-0.001	0.79		-2E-04	0.41		-0.004	0.13		-2E-04	0.41		0.01
	US1	0.004	0.07	.	9E-05	0.80		0.005	0.12		-0.001	0.57		0.02

Traders in financial futures

In the following table (Table 6), is an overview of the estimations for the positions from the TFF report, where we estimated the regression model onto the position of levered funds and asset managers/ institutional. We can see in both classifications a gap in the estimation of the reallocation signal in carry, here we had the same problem as described above, that we had no change in the signal in the regarded period, and could therefore not estimate the effect. In this analysis is the period of investigation from June 20, 2006 to February 26, 2019.

Table 6: OLS estimations for the classifications from the TFF

Overview of the estimations of the regression model with Q calculated from the classifications asset managers/institutional and levered funds. The table consists of the estimated betas of the reallocation from momentum and carry strategy (Coef. dmom and Coef. dcarry), the estimations for the coefficient of the first difference in the VIX index (dvix) and inverse volatility (inv vola) with the associated p-values and the coefficient of determination (R^2). To show the significance of the estimated betas we use the following notations: '.' , '*', '**', '***' stand for the significance of the coefficient on the 10%, 5%, 2.5%, and 1% level

	Ticker	coef dmom	p-value mom	coef dcarry	p-value dcarry	coef inv vola	p-value inv vola	coef dvix	p-value dvix	R^2
OLS financial futures - Asset managers /Institutional										
Currencies	BP1	0.020	0.06 .	-0.008	0.66	0.001	0.07 .	-0.003	0.36	0.01
Currencies	EC1	0.026	0.04 *	-0.002	0.81	-4E-04	0.14	-0.005	0.00 ***	0.02
Currencies	CD1	0.039	0.01 **	0.014	0.06 .	-0.001	0.13	-0.001	0.70	0.06
Currencies	AD1	0.024	0.16			0.001	0.33	-0.001	0.70	0.06
Currencies	JY1	0.015	0.36			-4E-05	0.94	-6E-05	0.93	0.00
Currencies	NV1	0.047	0.01 **			0.001	0.33	-0.006	0.03 *	0.03
Currencies	SF1	0.006	0.78	-0.013	0.00 ***	-1E-03	0.02 **	-0.005	0.01 **	0.07
Fixed Income	TU1	-0.001	0.78	-0.005	0.07 .	4E-05	0.22	0.002	0.15	0.01
Fixed Income	FV1	-0.002	0.45	-0.001	0.83	6E-05	0.71	0.002	0.37	0.00
Fixed Income	TY1	-0.005	0.26	0.001	0.78	3E-04	0.38	0.004	0.02 *	0.04
Fixed Income	US1	-0.001	0.61	-2E-19	0.93	-0.001	0.19	0.000	0.62	0.00
OLS financial futures - Levered Funds										
Currencies	BP1	-0.009	0.60	-0.007	0.01 **	0.002	0.04 *	0.009	0.01 **	0.02
Currencies	EC1	0.004	0.27	-0.001	0.29	0.001	0.47	0.001	0.59	0.00
Currencies	CD1	0.000	0.94	-0.003	0.71	0.002	0.24	-0.015	0.00 ***	0.03
Currencies	AD1	0.007	0.42			-3E-04	0.58	-0.018	0.00 ***	0.04
Currencies	JY1	0.012	0.00 ***			-1E-04	0.89	0.016	0.00 ***	0.05
Currencies	NV1	0.002	0.59			0.003	0.22	-0.006	0.19	0.00
Currencies	SF1	-0.001	0.71	0.018	0.00 ***	-0.001	0.32	0.008	0.23	0.03
Fixed Income	TU1	0.001	0.87	-0.001	0.77	-5E-05	0.16	0.00	0.94	0.00
Fixed Income	FV1	0.006	0.25	-0.003	0.07 .	-1E-04	0.32	-0.001	0.67	0.02
Fixed Income	TY1	0.010	0.01 **	0.006	0.15	-0.001	0.05 .	-0.004	0.01 **	0.04
Fixed Income	US1	0.002	0.97	3E-19	0.72	-3E-04	0.58	0.001	0.70	0.01

We see in Table 6 that neither one of the reallocation signals is overall able to explain the change in the net trading measure. By looking at the estimation for the betas of the change in the momentum signal (column "dmom") of the classification asset manager/ institutional we see that it is positive and partly significant in the currencies-, but negative and not significant in the fixed income futures market. In the classification of levered funds, the coefficients are positive, except for British pound (BP1) and SF1, but significant for Japanese Jen (JY1) and the US 10 year T-Notes (TY1).

By comparing the betas for the reallocation signal of carry, we also found that it is not able to explain neither the change in of the position in currency or fixed income futures markets, for both classifications. More precise, are the only values significant in Canadian Dollar (CD1), Swiss Franc (SF1), and US 2 year T-Notes (TU1) in the classifications of asset managers/institutional traders. For the classification of levered funds, it is British pound (BP1), SF1, and FV1.

The estimations for the coefficient for the inverse volatility is also not able to explain Q overall and only in some cases. The values are significant for the following three futures markets across both classifications: BP1, SF1, and TY1. By the change in the proxy of the risk appetite (column “dvix”), it seems that it has overall the most significant impact on Q in the classifications of the TFF reports with mostly negative estimated betas. Looking at the coefficient of determination, we found that the result is not satisfying since the independent variables are on average, not able to explain more than 4% on average.

4.2.3 Testing and Model Assumptions

By estimating linear regression models, we have to regard the assumptions of the model. Which are: (i) Mean, and variance are constant over time, (ii) Residuals are normally and independently distributed

If any of the assumptions mentioned above are not fulfilled, then the regression results are not viable, meaning that the estimations are spurious and should not be interpreted o used. Normally the assumptions are checked by plotting the residuals in different ways. Since we estimated 77 regressions, we cut some edges in controlling the residuals, by only controlling a sample of the regressions for the classification of non-commercial traders. To be more precise, we checked the residuals for the following futures: crude oil (CL1), Silver (SI1), wheat (W1), soybean oil (BO1) and lean hogs (LH1), Swiss franc (SF1) and US 2-year T-Notes (TU1).

First, we checked if the mean and variance are constant over time. Since we transformed the data and only used the first difference of the variables, we made the time series stationary and eliminated the trend. By plotting the residuals, we found that the mean is constant. To check the variance, we calculated the standard deviation in a rolling window and found that this assumption is also fulfilled. To check if the residuals are normally distributed, we plotted a QQ-plot. The QQ-Plot is a tool that plots the residuals against the standard normal distribution. We found that this assumption is also approximately fulfilled. Thirdly, we checked for autocorrelation. We did this by calculating the Durbin-Watson test statistics, which takes the values from zero to four. A value of two means that there is no autocorrelation in the data, a value of four means that the residuals are perfectly negatively autocorrelated and a value of zero means that the residuals are perfectly positively autocorrelated. In our sample, we got all values around two, which means we have no autocorrelation in the residuals and that this assumption is also fulfilled.

4.2.4 Summary of the Estimations

We chose two different periods of investigation because the more specified reports were implemented at a later date. We examined the period from November 26, 1997, to February 26, 2019, for the classification of non-commercial traders, and the period of June 20, 2006, till the February 26, 2019for the other classifications.

To measure the impact of the reallocation signals, we used multiple OLS regression. For the commodity markets, we found that the reallocation signal from the momentum strategy has a positive and significant impact on Q, meaning that a change from a buy to a sell signal increases the change in the net trading position.

The estimation for the carry reallocation signal, in commodity markets, are mixed. We found positive and negative significant estimations for the beta, especially in the agricultural sector, for both classifications. Negative estimations for beta mean that a change from a sell to a buy has a negative impact on Q. The negative estimations are contradicting with what we expected. The insignificant estimations for the betas could arise from the fact that the term structures do not change too often, which leaves us with only a few reallocation signals, which are not able to explain the weekly change of the position of the traders. By comparing the estimated coefficients for the reallocation signal of carry and momentum, we found that the estimated coefficients for the carry and momentum signal in absolute terms are higher for the significant values for the classification of managed money. This finding seems reasonable because the classification of managed money is a subclass of the non-commercial traders and is thus more specified.

The results for the financial futures are somewhat disillusioning because neither of the reallocation signals from the momentum or the carry strategies can explain the change in the net trading measure Q in the fixed income futures in all the regarded classifications.

By examining the classification of non-commercial traders in financial futures, we found that the reallocation signal from the momentum strategy has an overall positive and significant impact on Q. In the classification of asset managers/institutional the significant coefficients are higher, compared to the classification of non-commercial traders, meaning that the impact on a change in the signal is higher on the more specified classification. However, this effect cannot be seen in the classification of levered funds, we found that none of the used variables can overall explain the change in the position of the traders.

The estimations for the beta of the inverse volatility have a significant impact in the sector of agricultural and partly energy commodity futures but fails to explain the change in financial futures overall. The estimations for the coefficient of the change in the risk appetite (VIX index), align overall with the findings in the literature, where the coefficients are negative. The negative impact means that when the VIX increases, it has a negative impact on the change of the net trading position.

The coefficient of determination is overall small, meaning that the used variables only can partially explain the variability of the change in the net trading measure. We conclude that the reallocation signals, as well the VIX index and the first difference of the inverse volatility can play a role in explaining the change of the positions but are overall insufficient to explain the whole variability. Reasons for that are as mentioned above, that the change in the signal does not change every week, but the traders' position do.

5 Discussion and Outlook

5.1 Summary and Conclusion

In the examination of recent papers, we found that the literature about the relationship of prices, volatility, returns, and the positions of traders is thoroughly researched. However, the results do somewhat contradict each other, in terms of if the found effects should be positive or negative. Moreover, we found a gap in the literature regarding the effects of reallocation the position due to a change in the trading signals. We contribute to the literature by researching this effect with trading signals from momentum and carry strategies. In addition to the reallocation signals, we added a global variable proxy for the risk appetite (VIX index) and the change in the inverse volatility. The inverse volatility can be used to weight the assets in a portfolio.

We examined this effect in 33 futures markets, where 22 are commodity, seven are currency and four are fixed income futures. We focused on speculative traders and estimated the impact on four different classifications, where one classification covers all futures markets, two of the classifications are only for the financial futures, and one is only for commodity futures.

In our empirical results, we first compared the performance of the momentum-, carry, and long-only strategies, and we found that the momentum strategy works the best overall. The carry strategy performed best in the energy and agricultural sectors, as well as partly in the currency and fixed income markets. The long-only strategy was able to outperform both strategies in the fixed income market as well as the commodity sector of metal futures. In a second analysis, we examined the positions of the traders; we found that an increase in the net long position is due to a rise in the long positions and a simultaneous decrease in the short positions. This finding lead simplified the statistical modeling since we can only focus on the net trading measure Q. By looking at the movement across the markets, we found that futures which belong to the same sector or market have a higher correlation. This means that if the position of the aggregate traders increases in a specific futures market, the positions in the same sector are also going to increase.

In the statistical analysis, we found that the reallocation signal from the momentum strategy has a positive and significant effect in all commodity futures markets on the position of traders for both classifications (non-commercial traders and managed money). In the same classifications, the reallocation signal from the carry strategy has a significant and positive effect in most agricultural commodities, except for some cases, where the effect is negative.

In the financial futures, the results vary a lot across the classifications. The estimations of the beta for the reallocation signal of the momentum strategy is significant for all the currencies in the classification of non-commercial traders and partly significant for the classification of asset managers/ institutional, however, the effect is mostly insignificant in the classification of levered funds. The reallocation signal from the carry strategy is positive and significant for all currencies in the classification of non-commercial traders and mostly insignificant for the other two classifications. In the fixed income futures markets most of the estimated betas were not significant for both reallocation signals.

Our findings for the estimation of the first difference of the VIX index is that if it is significant than it is mostly negative, which aligns with the findings in the literature. The estimations of the beta for the first difference of the inverse volatility are mixed because the significant values are overall mixed because in the sector of metals the effect is positive and significant, whereas in the agricultural sector the estimations are significant and negative. In the financial futures the effect is mostly insignificant.

In summary, we accept the null hypothesis for the reallocation signal of the momentum strategy for the commodity and currency futures of the classifications of non-commercial traders and the classification of managed money, but decline it partly for the classification of asset managers and decline it overall for the classification of levered funds. For the reallocation signal from the carry strategy, we accept it overall for the agricultural futures in the classification of non-commercial traders and managed money, but decline it for all the other classifications.

5.2 Critical Appraisal

We overcame the problem of different periodicities in the data (VIX index and price data were daily, whereas the publications have a weekly periodicity) by calculating a rolling mean of the price data and estimated the lagged data of one day onto the position of the traders. In retrospective, this problem could have been overcome by calculating the signals every week. Moreover, we neglected real-world frictions like transaction costs and illiquidity of futures, when we calculated the trading signals.

By estimating the regression models, we had the problem that some reallocation signals from the carry-strategy were singular, meaning that over the whole period, there was no change from buy to sell or the other way. Therefore we had to adjust the regression model and exclude the carry signal. Another problem that we neglected in this thesis is that we found that the coefficient of determination was overall small, meaning that we only were able to explain the variability in the dependent variable partly, this leads to an omitted variable bias, which means that variables which maybe were necessary to explain the dependent variables were omitted.

Another interesting aspect which we could not cover in this analysis is to estimating the effects over whole sectors because we did not find appropriate panel regression techniques, which would not violate the assumptions.

5.3 Implications for the Practice

An important finding for the practice is that we found that both reallocating signals have a significant impact on the traders' position in the sector agricultural futures in the classification of non-commercial traders. Those findings are new and have not yet been researched. We think that these results are a milestone in explaining ex-post the traders' movement with reallocation signals. For the practice, we advise focussing on agricultural commodities because both reallocation signals had a significant impact. Since ex-post the effect is significant we think it could also work to predict the movement of the aggregated traders because if this worked, we would have a new indicator for the futures prices.

5.4 Implications for the Research

We think it is interesting to research the whole market of fixed income futures again since most of the used variables were not significant in the regression analysis, and we are almost certain that other trading-like signals exist that could help to estimate the effect on the traders' position. Moreover, we think that one should also focus on the classification of levered funds and asset managers/ institutional because our results were not able to estimate significant effects overall. For the classification of levered funds, we believe that perhaps more sophisticated trading signals that could help to measure the effect on the traders' position. Another aspect is that we researched all the markets ex-post, it could be interesting to use the trading signal to predict the change in the position. However, we think to do so; one should use more explanatory variables, meaning more trading signals and maybe also whole portfolio reallocation signals. Speaking of the portfolio, we also believe that it could be interesting to measure the effects over whole sectors and not for every market individual because we found that the correlations of the traders’ position across the same sector are higher than other futures markets.

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7 Appendix

7.1 Data Sources and Tables

The following tables give a summary of the data which we use in this thesis. The first Table 7, gives a summary of the positions and reports as well as asset classes, which we analyze. We further downloaded for each Classification, the long and short position and once the overall total open interest.

Table 7: Overview of the COT reports

The following overview of the reports consists of the name of the report (*Report Name*), the class (*Classification*) which we analyze within this thesis, the *asset class* which shows what futures are regarded within the position, and the *start date*

COT Reports

Report Name	**Classification**	**Asset classes**	**Start Date**
COT	non - commercials	all	November 11, 1997
DCOT	Managed Money	commodities	June 20, 2006
TFF	Asset Managers/ Institutional	financial	June 20, 2006
TFF	Levered Funds	financial	June 20, 2006

The data source of the futures contracts is given in the following Table 8. the dataset compromises 33 US futures contracts. Whereas 22 are commodities, 7 are currencies, and 4 are US fixed income futures.

Table 8: Overview of the futures contracts

The following table gives an overview of the futures, which we analyze in this thesis. The futures are organized by the type of market and in case of commodities, as well by the sector. The table consists out of the Name of the futures market, the ticker, and the source, respectively the exchange.

Futures – Data sources

Market/ Sector	Ticker	Name	Exchange
Commodity/ Energy	CL1	Crude Oil, Light Sweet	Intercontinental Exchange (ICE)
	XB1	RBOB Gasoline	New York Mercantile Exchange (NYMEX)
	NG1	Natural Gas, Henry Hub	New York Mercantile Exchange (NYMEX)
	HO1	Heating Oil	New York Mercantile Exchange (NYMEX)
Commodity/ Metals	GC1	Gold	New York Commodities Exchange (COMEX)
	SI1	Silver	New York Commodities Exchange (COMEX)
	PL1	Platinum	New York Commodities Exchange (COMEX)
	HG1	Copper, High Grade	New York Commodities Exchange (COMEX)
Commodity/ Agricultural	CT1	Cotton No.2	Intercontinental Exchange (ICE)
	KC1	Coffe 'C'	Intercontinental Exchange (ICE)
	SB1	Sugar #11	Intercontinental Exchange (ICE)
	JO1	FCOJ-A (Frozen Orange Juice)	Intercontinental Exchange (ICE)
	CC1	Cocoa	Intercontinental Exchange (ICE)
	W1	Wheat	Chicago Board of Trade (CBOT)
	KW1	KC Hard Red Wheat	Chicago Mercantile Exchange (CME)
	S1	Soybeans	Chicago Board of Trade (CBOT)
	C1	Corn	Chicago Board of Trade (CBOT)
	BO1	Soybean Oil	Chicago Board of Trade (CBOT)
	SM1	Soybean Meal	Chicago Board of Trade (CBOT)
Commodity/ Live stock	FC1	Feeder Cattle	Chicago Mercantile Exchange (CME)
	LH1	Lean Hogs	Chicago Mercantile Exchange (CME)
	LC1	Live Cattle	Chicago Mercantile Exchange (CME)
Currencies	BP1	British Pound	Chicago Mercantile Exchange (CME)
	EC1	Euro FX	Chicago Mercantile Exchange (CME)
	CD1	Canadian Dollar	Chicago Mercantile Exchange (CME)
	AD1	Australian Dollar	Chicago Mercantile Exchange (CME)
	JY1	Japanese Yen	Chicago Mercantile Exchange (CME)
	NV1	New Zealand Dollar	Chicago Mercantile Exchange (CME)
	SF1	Swiss Franc	Chicago Mercantile Exchange (CME)
Fixed Income	TU1	US T-Notes, 2-Year	Chicago Board of Trade (CBOT)
	FV1	US T-Notes, 5-Year	Chicago Board of Trade (CBOT)
	TY1	US T-Notes, 10-Year	Chicago Board of Trade (CBOT)
	US1	US T-Bonds, 30-Year	Chicago Board of Trade (CBOT)

7.2 Annualized Mean and Distribution of the Returns

Table 9: Summary statistic of the return distribution of the futures

Summary statistic of the return distribution of the commodity futures,. This table gives an overview of annualized mean returns, kurtosis (kurt), and skewness (skew) per strategy (Momentum, Carry and long-only) and specific market (Ticker). The Time interval of this analysis is from November 11, 1997 till February 26, 2019. Except for ‘XB1’ is the start date the March 2, 2006, for EC1 it is the May 19, 1999 and for the NV1 it is the June 18, 2002.

Annual mean returns and return-distribution

	Ticker	#years	Momentum			Carry Strategy			long-only Strategy		
			Ann. Mean	Skew	Kurt	Ann. Mean	Skew	Kurt	Ann. Mean	Skew	Kurt
Energy	CL1	21.3	7.5%	-0.13	7.3	5.9%	-0.01	3.4	-0.3%	0.00	3.4
	XB1	12.2	3.4%	0.06	8.0	3.8%	-0.07	2.9	7.0%	0.00	3.0
	NG1	21.3	-2.4%	0.43	15.9	-11.9%	0.08	6.1	-21.5%	0.55	6.1
	HO1	21.3	9.7%	0.19	5.9	0.0%	-0.03	2.3	5.4%	0.08	2.2
Metals	GC1	21.3	0.1%	-0.51	13.8	-3.5%	0.08	7.9	4.5%	0.10	7.9
	SI1	21.3	-1.2%	-0.32	16.8	-8.4%	0.17	7.6	2.9%	-0.72	7.5
	PL1	21.3	3.4%	-0.73	19.2	3.3%	0.02	10.5	4.2%	-0.07	10.3
	HG1	21.3	4.5%	-0.01	10.5	0.2%	-0.14	4.1	3.6%	0.02	4.1
Agricultural	W1	21.3	-2.3%	-0.09	4.6	5.9%	-0.08	2.7	-12.9%	0.14	2.7
	KW1	21.3	3.4%	-0.10	3.9	10.5%	-0.11	2.0	-9.2%	0.22	2.0
	S1	21.3	0.7%	-0.17	5.2	5.0%	0.06	2.6	2.5%	-0.03	2.6
	C1	21.3	0.2%	-0.16	5.9	1.1%	-0.09	2.6	-8.7%	0.17	2.6
	BO1	21.3	1.7%	-0.11	5.3	-3.5%	-0.19	2.4	-4.0%	0.24	2.4
	SM1	21.3	0.2%	-0.12	4.1	-4.0%	0.01	2.1	9.2%	0.08	2.1
	CT1	21.3	4.5%	-0.02	3.8	2.3%	-0.07	1.8	-7.7%	0.08	1.8
	KC1	21.3	-3.6%	-0.41	6.7	1.7%	-0.57	7.4	-13.2%	0.61	7.4
	SB1	21.3	3.8%	-0.19	4.3	0.1%	-0.09	1.6	-4.5%	-0.03	1.6
	JO1	21.3	-1.0%	-0.26	9.0	-11.7%	-0.74	10.9	-2.7%	0.72	10.9
	CC1	21.3	-5.3%	-0.65	5.7	-2.4%	-0.20	2.5	-3.2%	0.01	2.5
Live-stock	FC1	21.3	1.3%	0.05	4.3	-1.2%	-0.13	1.6	1.0%	-0.12	1.6
	LH1	21.3	-0.4%	0.06	4.7	-6.4%	-0.07	1.3	-13.2%	0.04	1.3
	LC1	21.3	1.1%	-0.07	3.2	-4.0%	-0.21	1.4	-1.4%	-0.05	1.4
Currencies	BP1	21.3	0.3%	0.51	8.9	-0.8%	-0.83	10.3	-0.5%	-0.81	10.3
	EC1	19.8	2.2%	-0.21	3.8	2.9%	0.02	1.7	-0.5%	0.12	2.3
	CD1	21.3	0.6%	-0.19	8.1	-2.5%	-0.03	3.1	0.4%	-0.04	3.1
	AD1	21.3	2.1%	-0.19	21.2	2.8%	-0.28	8.2	2.1%	-0.17	8.2
	JY1	21.3	1.0%	-0.45	10.4	-1.7%	0.64	8.8	-1.7%	0.64	8.8
	NV1	16.7	2.0%	0.09	7.4	5.8%	-0.38	3.3	6.1%	-0.38	3.3
	SF1	21.3	-2.4%	-11.05	20.7	-0.2%	4.61	10.2	-0.2%	4.65	10.4
Fixed Income	TU1	21.3	0.8%	0.06	12.7	0.2%	-0.25	7.5	1.1%	0.14	7.5
	FV1	21.3	1.2%	-0.23	6.3	1.0%	0.00	3	2.4%	-0.13	3.0
	TY1	21.3	1.1%	-0.07	5.1	2.1%	0.06	2.8	3.5%	-0.01	2.8
	US1	21.3	-0.5%	0.18	5.6	4.1%	0.01	2	4.1%	-0.03	2.0

7.3 Comparison of Non-Commercials Traders and Money Managers

We compare the money managers with the non-commercials since we are not researching another commodity classification. The results are in Table 10. We compare arithmetic mean, standard deviation, and the 5% and 95% quantiles.

Table 10: Summary statistics of the change Q for both classifications of commodity futures

Summary statistics of the change in the net long position of the two classifications non-commercials and managed money. The summary statistics consists of the arithmetic mean (mean), standard deviation (stdv), and the 5% and 95% quantile values, for both classifications and every financial futures contract, that is regarded. The period is from June 20, 2006, to February 26, 2019.

		COT and DCOT							
		Non Commercial Traders				Managed Money			
	Ticker	Mean	Stdv	5%	95%	Mean	Stdv	5%	95%
Energy	CL1	0.000	0.006	-0.009	0.010	0.000	0.027	-0.040	0.044
	XB1	0.000	0.010	-0.016	0.015	0.000	0.053	-0.093	0.077
	NG1	0.000	0.006	-0.009	0.010	0.002	0.038	-0.057	0.066
	HO1	0.000	0.010	-0.017	0.016	0.001	0.035	-0.061	0.055
Metals	GC1	0.000	0.019	-0.033	0.033	0.001	0.068	-0.117	0.114
	SI1	0.000	0.017	-0.028	0.027	0.002	0.097	-0.159	0.160
	PL1	0.001	0.026	-0.042	0.039	-0.007	0.352	-0.591	0.600
	HG1	0.000	0.016	-0.023	0.026	0.003	0.163	-0.278	0.282
Agricultural	CT1	0.000	0.013	-0.020	0.022	-0.001	0.053	-0.075	0.091
	KC1	0.000	0.013	-0.022	0.023	-0.002	0.071	-0.115	0.116
	SB1	0.000	0.014	-0.023	0.024	0.000	0.059	-0.086	0.102
	JO1	0.000	0.012	-0.019	0.019	0.000	0.040	-0.059	0.073
	CC1	0.000	0.015	-0.027	0.022	-0.001	0.054	-0.084	0.091
	W1	0.000	0.015	-0.023	0.024	-0.001	0.060	-0.085	0.105
	KW1	0.000	0.018	-0.028	0.030	-0.002	0.042	-0.074	0.076
	S1	0.000	0.015	-0.025	0.027	-0.003	0.062	-0.104	0.113
	C1	0.000	0.011	-0.016	0.019	-0.001	0.035	-0.046	0.064
	BO1	-0.001	0.027	-0.046	0.041	-0.001	0.030	-0.048	0.048
	SM1	0.000	0.014	-0.023	0.021	-0.001	0.050	-0.097	0.067
Live-stock	FC1	0.000	0.016	-0.026	0.026	-0.001	0.056	-0.091	0.088
	LH1	0.000	0.011	-0.018	0.018	-0.002	0.034	-0.051	0.057
	LC1	0.000	0.011	-0.017	0.018	0.003	0.029	-0.047	0.051

In terms of the threshold of the percentile values are consistently absolute huger for traders classified as managed money, which can be seen as an indicator, that this class is more homogenous than the type of non-commercial traders. The reasoning is that the values vary more because the traders move in the aggregate into the same direction.

Moreover, we can see that the mean over time for non-commercials are approximately zero with no exceptions further is the standard deviation smaller than for the class of managed money.