Trading Strategies and Return Patterns in Commodity Futures Markets

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Abstract

This thesis analyzes commodity futures pricing, trading activities in commodity futures contracts and their use for investment strategies. The aim of this thesis is to fill important gaps in the research field of commodity markets and to highlight special characteristics of commodity futures. It consists of three main chapters which are based on three research papers.

The first paper *Smart Beta Strategies on Commodity Futures Markets* analyzes the use of commodity futures for passive long-only factor investment strategies. It builds on the idea of using factor investment strategies, sometimes also called smart beta strategies, in the space of commodity futures markets. This paper identifies and analyzes eight different types of smart beta strategies, including equal-weight, low-volatility, momentum and term-structure strategies. Term structure strategies can provide an excess return of up to 25% p.a. in the sample-period and prove to be a very attractive investment strategy. These results also cannot be explained by known equity or bond risk-factors. These results highlight the possible information content of the term structure of futures prices and also provide the idea for the second research paper.

The second paper *A Factor Decomposition of Term Premiums in Commodity Futures Markets* examines the term structure of expected commodity futures returns on a theoretical and empirical basis. We use a 3-factor model, which is based on the Cortazar N-factor model, to decompose commodity futures term premiums into a constant, a linear and a non-linear function for the time to expiry. We show that commodity futures returns for maturities of one month and up to twelve months are well explained by this model. Furthermore the information of this model can also be used for profitable long-short trading strategies with Sharpe ratios up to 0.93.

The third paper *Short Term Commodity Futures Contracts: Trading Patterns and Returns* analyzes the specific behaviour of commodity futures in the last trading months, when trading activity is possibly influenced by the physical delivery process. The physical delivery process is usually avoided by financial investors. In our study we analyze trading patterns in volume, open interest and futures returns based on differences in the timing of the physical delivery process for different commodities. We find that the notice day presents an important turning point for every commodity futures contract, when the contract turns from an actively traded contract to a very illiquid contract. Furthermore, we also show that long investors who are willing to run the risk of physical delivery can earn a risk premium during the notice period.

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1 Introduction

Commodity futures represent a fascinating, yet not fully understood asset class. Although a futures contract is by definition relatively simple compared to for example options, swaps or even more complex instruments, the heterogeneous underlying physical assets add a special layer of complexity.

During the last two decades commodity futures have already been the subject of intensive research. Nevertheless, the pricing of commodity futures contracts is not yet fully understood. Commodity futures have often been observed to generate positive returns but can they also be profitably used in a passively managed portfolio? Another aspect that is often overlooked is the term structure of commodity futures returns. Commodity futures present the investor with a wide range of different contracts with different expiry dates for each commodity. The range of contracts for one commodity are close substitutes, but they are not identical. Hence, it is important to analyze differences and the specific focus will be on modeling the term structure of expected futures returns. Finally it is also important to analyze the trading patterns at the short-term end of a commodity futures contract. How are the trading activities and returns influenced by the nearing expiry of the futures contract? These research aspects are of interest for many market participants like investors, risk-managers, hedgers and producers of commodities.

Structure and Objective of the Thesis

This dissertation aims to fill important gaps in the understanding of commodity futures pricing, trading activities in commodity futures contracts and their use for investment strategies. As stated above, the findings of this thesis are not only relevant for researchers but also for practitioners who work in asset management or risk management. Each chapter focuses on a different aspect of commodity futures and their special properties and usecases.

Chapter 2 *Smart Beta Strategies on Commodity Futures Markets* is an empirical analysis of long-only passive investment strategies for commodity futures. The aim of this paper is to find out if commodity futures can be profitably used in long-only passive factor investing strategies. Although long-short strategies can be applied re-

latively easily in commodity futures and there is a large body of research on mostly long-short strategies (for example Erb and Harvey (2006), Miffre and Rallis (2007), Fuertes et al. (2010) and Miffre (2016)) this paper focuses on a more traditional long-only approach which is comparable to traditional investing in for example equities. The idea of this paper is to take the concept of factor investing from equities and try to apply it to commodity futures. In this context it is natural to use long-only strategies because traditional investors, who are interested in index investing and factor strategies, tend to have a preference for clear and easy to understand long-only strategies.
The paper analyzes equal-weight, momentum, low-volatility and term-structure strategies. While equal-weight, momentum and low-volatility strategies are well-known strategies for equities, the term-structure strategies are entirely commodity specific. The idea is to use information from the term-structure of futures prices to find the most attractive commodities. Commodity futures which are in backwardation could potentially converge to a higher spot price when they are nearing expiry, which should provide the long investor with an attractive return. While the idea here is certainly not new and has been analyzed before, the contribution of this paper is rather to analyze and showcase how commodity futures can be used in a consistent framework of long-only investments in addition to equities and bonds. It is also analyzed whether well-known risk-factors from other asset classes can explain the returns of these strategies.

Chapter 3 *A Factor Decomposition of Term Premiums in Commodity Futures Markets* is a theoretical and empirical study of the term structure of expected futures returns. The aim of this paper is to gain new insights into term premiums in commodity futures. The term structure of futures returns is an aspect of commodity futures that is often overlooked. Market participants can choose from a wide array of futures contracts for the same commodity with different expiry dates. It seems natural to ask whether and how they differ when it comes to the return structure of these contracts. Due to unobservable expected returns and very noisy commodity futures returns it is difficult to quantify expected commodity futures returns. Existing commodity futures pricing models developed by Schwartz and Smith (2000) or Cortazar and Naranjo (2006) are widely accepted and used to derive the risk neutral futures prices. However, as Cortazar et al. (2015) points out, these models can also be used to derive expected prices under the physical measure. These expected prices under the physical measure also give us the opportunity to calculate expected

returns.
A particular challenge when estimating the N-Factor Model by Cortazar and Naranjo (2006) is that some parameters, especially the risk premiums, can only be estimated with large errors. Cortazar et al. (2015) solve this problem by using the CAPM to estimate expected commodity futures returns and use them as a restriction in the Schwartz and Smith (2000) model. In our paper we present a different approach, which is not relying on an external model or external information for restrictions. If we focus on the expected returns, we can derive an expression for the expected returns from the model that significantly reduces the number of estimated parameters and still provides flexibility in modeling the term structure. The model allows us to differentiate between a level-, a slope- and a curvature-factor to accurately fit the term structure of expected futures returns. Based on these three-factors we are also able to construct and analyze profitable investment strategies. The most stable trading strategies are based on information about the curvature of the expected return curve.

Chapter 4 *Short Term Commodity Futures Contracts: Trading Patterns and Returns* is an empirical study of the trading activities in short-term commodity futures contracts. Prior results have shown that some commodities experience high returns in the very last month before expiry. In this paper we want to take a deeper look in the trading activities in the last months before expiry. Trading activities are potentially influenced by the physical delivery process of commodities. In our paper we do not want to focus on rolling strategies as for example Mou (2011). Instead we will argue that long investors are bearing the risk of physical delivery during the notice period which is a possible explanation for higher returns for long investors during the last month.
We compare three commodities (crude oil, gold and corn) which all have different time periods for the position period, the notice period and the delivery period. In our analysis, we compare the structures in trading volume, open interest and returns for these commodities and link these differences to a different timing of the position and notice period.

2 Smart Beta Strategies on Commodity Futures Markets

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Abstract

Smart Beta strategies are a recent trend primarily developed in equity markets, potentially allowing investors to improve their asset allocation through factor tilting their portfolio. This paper analyzes eight smart beta strategies, including equal-weight, low volatility, momentum and term structure strategies for commodity futures markets using a recent dataset of the Commodity Research Bureau. The contribution of this study is threefold: Firstly, it gives an overview which smart beta strategies can be applied to commodity markets. Secondly, these strategies are analyzed with respect to their risk and return properties. Lastly, this study also analyzes the exposures to known risk factors in equity, bond, and commodity futures markets using a multi-factor regression model. The term structure strategies provide a geometric average excess return of up to 25% p.a., while other smart beta strategies do not generate similar returns. Known risk factors only explain a small fraction of these excess returns. Hence term structure strategies are an attractive investment opportunity and the term structure of commodity futures seems to contain valuable information for investors.

JEL Classification: G11

Keywords: smart beta, factor-investing, commodity futures

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2.1 Introduction

During the last two decades, investors' interest in the asset class of commodities has increased dramatically (Tang and Xiong, 2012). According to the Commodity Futures Trading Commission, the number of traded commodity futures contracts increased almost fivefold between 1998 and 2008 (CFTC, 2008).
A recent trend in equity markets is to use smart beta strategies. Smart beta strategies seek to optimise the risk and return profile of a passive index investment strategy by deviating from the market capitalisation weighting scheme of the most common equity indices (Amenc et al., 2012). It seems logical to try to link the approach of smart beta strategies with an investment in commodity futures. This paper analyzes the risk and return profile of different smart beta investment strategies on commodity futures markets. In general, this topic is within the research fields of asset management, index investments and commodity futures. The research question is:

> **Which long-term returns and risk factor exposures can investors expect from using smart beta commodity futures investment strategies?**

This research question contains three different aspects. First, it is unclear which smart beta strategies can be applied in commodity futures markets. Second, the expected returns of these strategies are of great interest for investors. Third, the risk exposure of these strategies should be examined. To answer the main research question, it should be divided into three questions covering the different aspects:

1. Which smart beta strategies can be defined for commodity futures?
2. What returns were achieved by applying these strategies in the past?
3. Are these strategies exposed to known risk factors?

Although investors can invest in commodities in many different ways (e.g., by buying commodities physically or buying stocks of commodity-producing companies), this paper will only focus on commodity futures markets. Further, the investors' perspective considered in this study will be a long-only perspective. It is not the intention of this study to investigate long-short strategies that are also discussed in the academic literature (Miffre, 2016). It is also not the focus of this paper to test the market efficiency of commodity futures markets.

First, the existing body of literature on commodity investments will be used to obtain an overview of the current state of research on commodity futures investment strategies. Second, the analyzed smart beta strategies will be introduced to answer the first aspect of the research question. The analyzed strategies include a commodity index strategy, an equal weight strategy, low volatility strategies, momentum strategies and term structure strategies. In addition to the information on the construction and implementation of the strategies, this section will provide a brief insight into why each strategy could add value for investors.

Third, the dataset used for the empirical analysis will be explained and described. The dataset encompasses a set of 25 commodity futures contracts for January 1989–January 2015. Hence, this analysis uses an up-to-date dataset including recent developments in commodity prices. Further, the data and the risk factors used for the risk factor analysis will be explained.

Finally, the results for the performance and risk analysis of the commodity futures smart beta strategies will be presented to answer the second and third aspects of the research question. The results will be compared to the expectations formed in the literature review to determine if they are in line and if there are any surprising results and insights into the commodity futures markets. The conclusion will briefly summarise the main findings of this analysis and provide directions for future research in the field of commodity investments.

2.2 Expectations on Commodity Futures Investment Strategies

Although commodity futures have been traded in England since the sixteenth century, research activity on investment strategies in these markets only began at the end of the twentieth century. It can even be argued that commodities are still a relatively unknown asset class (Gorton and Rouwenhorst, 2006). An overview of selected research papers that focused on, or at least touched, the research field of investment strategies on commodity futures markets is provided in Appendix 2.9. Appendix 2.10 briefly summarises the findings of these studies regarding the different strategies and standard performance measures, such as mean return, standard deviation and Sharpe ratio.

In general, the results of previous studies are rather homogenous. Past studies have found positive mean excess returns for various types of strategies on commodity futures markets (Bodie and Rosansky, 1980; Fama and French, 1987; Greer, 2000; Miffre and Rallis, 2007; Fuertes et al., 2010; Gorton and Rouwenhorst, 2006). Although the positive excess returns are not always significant, the results suggest that investments in commodities futures markets can generate positive excess returns in addition to the collateral return of a fully collateralised strategy. The following expectations can be drawn based on the previous research.

Expectation 1

> All commodity futures smart beta strategies are expected to yield positive excess returns.

Positive mean excess returns of investments in a portfolio of commodity futures are particularly interesting because previous studies have shown that individual commodities are highly unlikely to generate positive excess returns (Erb and Harvey, 2006). Another potential upside reported by previous studies is the positive skewness in the returns (Bodie and Rosansky, 1980). If individual commodity futures are not expected to generate a positive excess return, how can the positive excess returns of commodity futures portfolios be explained? One reason could be that commodity futures are not a homogenous asset class of rather similar assets. Instead, commodity futures have been shown to be rather uncorrelated.

Therefore, they can be described as a heterogeneous collection of assets bound together by the fact that they are either a raw material or a primary agricultural product (Bodie and Rosansky, 1980). The low correlations between the individual commodities are an ideal foundation for diversification benefits within the asset class of commodities. This diversification benefit, sometimes called diversification return, drives the excess returns of commodity futures portfolios.

Expectation 2

> Individual commodity futures are expected to not yield positive excess returns. The individual commodity futures returns should be rather uncorrelated.

Another reason for positive excess returns of smart beta strategies could be the efficiency of the different strategies. Previous studies have covered index strategies, equal weight strategies, momentum strategies and term structure strategies. While in most studies, all these strategies yielded positive excess returns, momentum and term structure strategies stand out as delivering the highest average returns. The exceptional performance of these strategies leads to two conclusions. First, the momentum effect exists on commodity futures markets and second, the term structure of commodity futures contracts contains valuable information for investors.
Still, there is some uncertainty about whether long-only strategies can generate significant positive excess returns. In particular, Miffre/Rallis showed that the short exposure to loser commodities is the main driver of the momentum returns (Miffre and Rallis, 2007). Conversely, Fuertes et al. showed that for a different period, the long exposure to the winner portfolio is actually the main driver of the momentum returns (Fuertes et al., 2010).

Expectation 3

> Momentum and term structure strategies are expected to yield the highest excess returns.

However, might these excess returns just be a compensation for risk? Research suggests that this is not the case. The Sharpe ratios of the momentum and term structure strategies suggest that investors are actually overcompensated for their risk (Fuertes et al., 2010).

Expectation 4

> Momentum and term structure strategies are expected to have the highest Sharpe ratios.

Risk factors for the equity and bond market cannot explain the returns of commodity futures portfolios. The only significant risk factors are inflation and the strength of the US dollar (Erb and Harvey, 2006).

Expectation 5

> Known risk factors from equity and bond markets cannot explain the returns of smart beta commodity strategies. Inflation risk and currency risk are expected to be a commodity-specific risk factor.

2.3 Smart Beta Commodity Futures Investment Strategies

The term smart beta is widely used as a general phrase for passive investment strategies that seek to optimise an index with regard to different properties. Sometimes these strategies are called alternative index investment strategies. To improve the index, smart beta strategies either change the stock selection of an index, the weighting of the constituents or both (Amenc et al., 2012). In many cases, smart beta approaches are used in equity markets. However, they can also be applied to bond or commodity markets.
In practice, there are many different smart beta strategies. Table 2.1 provides an overview of different types of strategies and lists examples for smart beta exchange-traded funds (ETFs). As Table 3.1 shows, smart beta strategies on equity markets can be roughly divided into five different categories: carry/dividend, value, equal weight, low volatility and momentum strategies. Each of these strategies uses its own unique set of weighting and/or selection criteria. In the past, smart beta products have been criticised for not being transparent enough in terms of their exact construction (Amenc et al., 2012).

This shortcoming of many smart beta products makes performance comparison

Table 2.1: Overview of Smart Beta Equity Strategies and Example ETFs

Types of Strategy	**Weighting/ Selection Criteria and Example Smart Beta ETF**	
Dividend	Dividend growth, dividend yield	ProShares S&P 500 Dividend Aristocrats, iShares Core High Dividend ETF
Value	Book value, sales, earnings etc.	iShares Edge MSCI World Value Factor
Equal Weight	Equal weight	db x-trackers S&P 500 Equal Weight
Low Volatility	Volatility	iShares Edge MSCI World Minimum Volatility
Momentum	Price momentum	iShares Edge MSCI World Momentum Factor

and benchmarking complicated and challenging. Investors should also be careful when choosing smart beta strategies because they can bring significant systematic

risk factor exposure and strategy-specific risk (Amenc et al., 2012).
When trying to transfer the different types of strategies to commodity futures markets, it is obvious that dividend and value strategies cannot be used for commodities because there are neither dividend payments nor classical value indicators (e.g., book-to-market ratio) for commodities. Although there are no dividends for commodities, term structure strategies can be viewed as a type of carry strategy that are at least similar to a dividend strategy. The other three types of smart beta strategies could potentially be used in commodity futures markets. Hence, these strategies will be examined in this paper. For the purpose of this study, every commodity futures trading strategy that modifies the weighting scheme according to a certain weighting principle that offers a reasonable possibility to generate an attractive risk to return profile will be considered a smart beta strategy, by exploiting an anomaly or using portfolio optimisation techniques.
Each strategy will be implemented by buying the second-nearest futures contract at the end of each month. At the end of the next month, the exposure is rolled over to the next second-nearest contract. Transactions costs are not regarded in this analysis.
In the absence of an initial investment in futures, returns are calculated as the relative price change in the futures price during the holding period (equation 2.1).

$$r_{i,t} = \frac{F_{i,t+1} - F_{i,t}}{F_{i,t}} \tag{2.1}$$

Further, the investor is assumed to execute a fully collateralised strategy. The collateral will be the risk-free asset. In this scenario, the futures returns can be interpreted as an excess return because the risk-free-rate is already earned by the collateral (Bodie and Rosansky, 1980).
Index Strategy
The first question raised when applying smart beta strategies to commodity futures markets is how to define the market. For commodity futures, there is no cap-weighted index, as there is no market capitalisation for commodity futures. Every long contract entered into by one trader must be offset by someone taking a short position. Therefore, the market capitalisation of the futures market must be zero (Black, 1976). Practitioners in the field of asset management suggest simply taking the existing global commodity indices as the market portfolio. Of course, this rather pragmatic approach lacks a theoretical foundation in contrast to a cap-weighted equity index.

For this study, the S&P GSCI was chosen as a benchmark index strategy. The S&P GSCI is one of the most widely-known commodity indices.

Equal weight strategy

The equal weight strategy is a very popular approach in commodity futures research. Many studies have successfully tested an equal weight strategy for commodity futures (Bodie and Rosansky, 1980). As the name suggests, the equal weight strategy gives equal weight to each commodity (equation 2.2).

$$w_i = \frac{1}{n} \tag{2.2}$$

In equity markets, the equal weight has been shown to generate better out-of-sample Sharpe ratios than many other optimal asset allocation principles. The estimation errors in other potentially better allocation strategies seem to erode the benefits (DeMiguel et al., 2007). Therefore, the equal weight strategy stands out as a simple but effective asset allocation strategy, which makes it a natural candidate for a smart beta strategy.

Low volatility strategy

In contrast to the equal weight strategy, the low-volatility strategy has not yet been studied extensively for commodity futures markets. When studying equity markets, low-volatility strategies are currently very popular. Baker et al. view the low-risk anomaly as one of the greatest anomalies in finance (Baker et al., 2011). The low-volatility anomaly states that portfolios of low-volatility stocks outperform portfolios of high-volatility stocks (Baker et al., 2011; Dutt and Humphery-Jenner, 2013). The low volatility anomaly is also closely linked to the low beta anomaly. Similar to the low-volatility anomaly, low beta stocks are also likely to outperform high beta stocks (Baker et al., 2011).

As low-volatility strategies apply an optimised weighting scheme to an index to reduce or minimise the volatility of a portfolio, they can be recognised as a smart beta strategy. However, a low-volatility strategy might generate risk exposure to other unwanted risk factors, such as sector risks (Amenc et al., 2012).

Within this study, two different low-volatility weighting schemes will be analyzed. The first strategy invests in the quintile of commodities with the lowest historical standard deviation during the last 60 months (LV-Top5). The determination of the weights is described by Equation 2.3.

$$w_{i,t} = \frac{1}{5} \text{ if } \hat{\sigma}_{i,t-1} \leq q_{0.2,\hat{\sigma}}, \text{ else } w_{i,t} = 0 \tag{2.3}$$

The second strategy uses a relative weighting scheme (LV-RV). The portfolio weights are obtained by comparing the estimated standard deviation of one commodity with the mean standard deviation of all commodities. If the standard deviation of one commodity ($\sigma_{i,t-1}$) is greater than the average deviation ($\bar{\sigma}_{t-1}$), the weight of this contract is zero. If the standard deviation is smaller than the average standard deviation, the weight is determined as the difference between the standard derivation ($\sigma_{i,t-1} - \bar{\sigma}_{t-1}$) divided by the sum of all commodity futures standard deviations that have a below-average standard deviation ($\sum_i \sigma_{i*,t-1} - \bar{\sigma}_{i*,t-1}$). $i*$ denotes all commodity futures with a below-average standard deviation. Equation 2.4 describes the determination of the weights for the relative volatility strategy.

$$w_{i,t} = \frac{\sigma_{i,t-1} - \bar{\sigma}_{t-1}}{\sum_i \sigma_{i*,t-1} - \bar{\sigma}_{t-1}} \text{ if } \sigma_{i,t-1} < \bar{\sigma}_{i,t-1}, \text{ else } w_{i,t} = 0 \tag{2.4}$$

Momentum strategies

Another well-known capital markets anomaly is the momentum anomaly. The momentum anomaly holds that stocks (or other assets) that have yielded a positive return in the past will continue to generate positive returns in the future. The opposite holds for the stocks that have yielded a negative return in the past. In other words, momentum describes the medium-term persistence of returns.

The existence of momentum on the US stock market was first shown by Jegadeesh/Titman (Jegadeesh and Titman, 1993). As set out in the literature review, momentum strategies have also been analyzed for commodity futures and were quite successful. The momentum strategies are also analyzed with two different weighting schemes: a quintile approach and a relative strength approach. The first strategy is a classical momentum strategy that buys the top quintile (MOM-Top5) commodity futures based on the returns of the past month (one-month ranking period) and holds these contracts for one month (one-month holding period). The determination of the weights is described by Equation 2.5.

$$w_{i,t} = \frac{1}{5} \text{ if } r_{i,t-1} \geq q_{0.8,r_{t-1}}, \text{ else } w_{i,t} = 0 \tag{2.5}$$

The second strategy is a relative strength strategy (MOM-RS). In contrast to the momentum top quintile strategy, the relative strength strategy does not limit the number of contracts. The relative strength determines the weights for each commodity future by comparing the return of the past month with the average return of all commodity futures in the past month. If the past return of one commodity ($r_{i,t-1}$) is smaller than the average past return ($\bar{r}_{t-1}$), the weight of this contract is zero. If the past return is greater than the average past return, the weight is determined as the difference between the past return ($r_{i,t-1}-\bar{r}_{t-1}$) divided by the sum of all commodity futures returns that generated an above-average return ($\sum_i r_{i*,t-1} - \bar{r}_{i*,t-1}$). $i*$ denotes all commodity futures with an above-average return. Equation (2.6) describes the determination of the weights for the relative strength strategy.

$$w_{i,t} = \frac{r_{i,t-1} - \bar{r}_{t-1}}{\sum_i r_{i*,t-1} - \bar{r}_{t-1}} \text{ if } r_{i,t-1} > \bar{r}_{t-1}, \text{ else } w_{i,t} = 0 \tag{2.6}$$

In comparison to the top quintile strategy, the relative strength strategy is able to give higher weights to commodity futures with an exceptionally high past performance. Therefore, it uses also the strength of the momentum signal to determine the weights, whereas the top quintile strategy uses a simple equal weight approach.

Term structure strategies

While the other strategies have been derived from known smart beta strategies on equity markets, term structure strategies are commodity futures-specific. These strategies aim to use signals from the term structure of commodity futures by buying backwardated commodity futures contracts. According to the hedging pressure theory, a backwardated futures term structure indicates that short hedgers dominate the market. The lower prices of the distant contracts will motivate investors and speculators to take long positions to supply the short hedging interest of, for example, commodity producers. In other words, the short hedgers are willing to pay an insurance premium to hedge their exposure (Fuertes et al., 2010).

As an example, let us assume that the spot price for a bushel (bsh) of corn is USD 350 and the one-month futures price for a bushel of corn is USD 340. If an investor decides to enter a long futures contract of corn for USD 340/bsh, they would make a profit as long as the spot price is greater than USD 340 /bsh after one month. This example illustrates the advantageous setting of a long position in a backwardated futures term structure.

The relative price difference between a futures contract with a shorter maturity and a longer maturity is also called implied yield or implied return (ir). In this case, the implied yield between the spot price and one-month futures contract is 2.94%. The implied yield cannot be earnt directly. The implied yield is the return that can be earned when the spot price remains constant and the futures price converges with the spot price at maturity.

Following the example, it is intuitive to design a trading strategy that systematically

buys backwardated commodity futures. To remain consistent with the low-volatility strategies and the momentum strategies, two different term structure strategies were analyzed for this study.
The first strategy is the term structure top quintile strategy (TS-Top5). Its construction and weighting scheme is analogue to the momentum top quintile strategy. However, the term structure strategy uses the implied yield at the end of the month instead of the past return. Also, the TS-Top5 strategy goes long in the top five commodity futures sorted by the implied return with an equal weight (equation 2.7).

$$w_{i,t} = \frac{1}{5} \text{ if } ir_{i,t} \geq q_{0.8,ir_t}, \text{ else } w_{i,t} = 0 \tag{2.7}$$

Consistent with the other strategies, the term structure strategies also buy the second-nearest futures contract at the end of the month. In the next month, the exposure is rolled over to the next second nearest contract. Fuertes et al. showed that the signals from the front end of the term structure seem to convey more information than do the more distant contracts (Fuertes et al., 2010). Hence, using the nearest contracts should yield the best results for investors.
The second strategy is the term structure relative backwardation strategy (TS-RB). Similar to the momentum strategies, this study intends to determine whether weighting the commodity futures with the relative backwardation improves the performance of the term structure strategies. If the implied yield of a commodity futures contract is greater than the average implied yield of all commodity futures ($\bar{ir}_t$), the weight is defined by the difference between the implied yield and the average implied yield divided by the sum of all above average implied yields ($\sum_{i*}(ir_{i*,t} - \bar{ir}_t)$).
If the implied yield of a commodity futures contract is smaller than the average implied yield, the weight will be zero. The determination of the weights is presented by Equation 2.8.

$$w_{i,t} = \frac{ir_{i,t} - \bar{ir}_t}{\sum_i ir_{i*,t} - \bar{ir}_t} \text{ if } r_{i,t} > \bar{ir}_t, \text{ else } w_{i,t} = 0 \tag{2.8}$$

By comparing the results of the two term structure strategies, this study aims to reveal whether the intensity of backwardation can be of value for investors.

2.4 Dataset

Commodity Futures

An important design decision when studying commodity futures markets is which commodity contracts and time period should be analyzed. There is a trade-off between a long price history and a broad selection of commodity contracts that fully represent the range of today's commodity markets (Erb and Harvey, 2006). All data on commodity futures prices in this study are taken from the database of the CRB (CRB infotech CD). While many commodity futures quotes start as early as 1959, many other important commodity contracts like crude oil, heating oil or rice are only available from a point in the 1980s. To include these important commodity futures, especially the energy contracts, the period for the dataset was December 1989–January 2015

Two conditions were defined for the selection of the contracts:

- a complete time series of futures prices without missing data from December 1989–January 2015

- only one contract per commodity.

The first condition was set to avoid interpolation/estimation of prices. Some strategies, like momentum or backwardation, rely heavily on the exact prices of the one- and two-month contracts. An interpolation of these prices could influence the results of those strategies. Therefore, all contracts should produce a complete futures price history for the period.

The second condition was set to avoid having two contracts for the same commodity that might be more or less perfectly correlated with each other. In such cases, the older and more established contract was selected for analysis.

Table 2.2 provides an overview of the commodity futures contracts included in the empirical analysis. It also provides an overview of the contracts that were available for December 1989–January 2015 but that were not included because they did not meet the conditions set out above.

Of 38 contracts available in the CRB database from 1989 onwards, 25 contracts were included in the analysis. Six contracts were excluded because of missing price data (aluminum, barley, flaxseed, pork bellies, propane and unleaded gas). Four contracts were excluded because there was only spot and/or forward price data available (Lead, Nickel, Tin and Zinc). The last three contracts were excluded because the same commodity was already represented by another contract (crude oil,

copper and sugar).
As Table 3.2 shows, the 25 contracts included in the analysis are either traded at the Chicago Board of Trade (CBOT), the Chicago Mercantile Exchange (CME), the New York Board of Trade (NYBOT), the New York Mercantile Exchange (NYMEX) or the Winnipeg Commodities Exchange (WCE).
For each commodity, there were 302 end-of-month price observations for the one- and two-month contracts from December 1989–January 2015. The monthly excess returns were calculated as the relative price change of one contract over one month. Therefore, the investor is assumed to enter a long two-month contract at the end of each month and settle this contract at the end of the following month. Of the 302 futures price observations, 301 monthly excess returns were calculated. The return can be interpreted as an excess return because the investor is assumed to hold a fully collateralised commodity futures portfolio.
The results for the monthly excess returns of individual commodity futures are shown in Table 2.3. Of the 25 commodities, only 11 had a geometric average return greater than zero, while the geometric average of the other 14 was below zero. Only 10 commodities showed an arithmetic average return significantly different from zero (at α=0.10). Feeder cattle, copper, live cattle, gasoil petroleum and soymeal had significant positive monthly returns while corn, lumber, lean hogs, rough rice and wheat even had significant negative monthly returns. The most profitable commodities in this sample were soymeal (geometric average of 1.00% p.m.), copper (0.67% p.m.) and Live Cattle (0.48% p.m.). In contrast, the least profitable commodities were Lumber (–2.10% p.m.), wheat (–1.88% p.m.) and corn (–1.84% p.m.).
In general, the results suggest that individual commodities' excess returns are close to zero. While portfolios of commodity futures are expected to generate significant positive excess returns, this cannot be asserted for individual commodity futures. These results are also consistent with previous research (Erb and Harvey, 2006).

Table 2.2: Overview of Commodity Futures Contracts

Commodity	**Quotes Start Date**	**CRB Symbol**	**Exchange**	**Comment**	**Included**
Aluminium	08.12.1983	AL	NYMEX	missing data in CRB	no
Barley	24.05.1989	WA	WCE	missing data in CRB	no
Canola	03.09.1974	WC	WCE		yes
Cocoa	01.07.1959	CC	NYBOT		yes
Coffee	16.08.1972	KC	NYBOT		yes
Copper	01.07.1959	HG	NYMEX		yes
Copper	01.07.1959	CU	NYMEX	contract discontinued in 1989	no
Corn	01.07.1959	C-	CBOT		yes
Cotton	01.07.1959	CT	NYBOT		yes
Crude Oil WTI	30.03.1983	CL	NYMEX		yes
Crude Oil Brent	24.07.1989	NB	ICE	double to Crude Oil WTI	no
Feeder Cattle	30.11.1971	FC	CME		yes
Flaxseed	18.11.1980	WF	WCE	missing data in CRB	no
Gas Oil Petroleum	03.06.1986	LF	ICE		yes
Gold	31.12.1974	GC	NYMEX		yes
Heating Oil	14.11.1978	HO	NYMEX		yes
Lead	n/a	-	-	only spot and forward prices	no
Lean Hogs	28.02.1966	LH	CME		yes
Live Cattle	30.11.1964	LC	CME		yes
Lumber	01.10.1969	LB	CME		yes
Nickel	n/a	-	-	only spot and forward prices	no
Oats	01.07.1959	O-	CBOT		yes
Orange Juice	01.02.1967	JO	NYBOT		yes
Palladium	03.01.1977	PA	NYMEX		yes
Platinum	04.03.1968	PL	NYMEX		yes
Pork Bellies	18.09.1961	PB	CME	missing data in CRB	no
Propane	21.08.1987	ON	NYMEX	missing data in CRB	no
Rough Rice	20.08.1986	RR	CBOT		yes
Silver	12.06.1963	SI	NYMEX		yes
Soybean meal	01.07.1959	SM	CBOT		yes
Soybean Oil	01.07.1959	BO	CBOT		yes
Soybeans	01.07.1959	S-	CBOT		yes
Sugar #11	04.01.1961	SB	NYBOT		yes
Sugar #14	07.07.1987	SE	NYBOT	double to Sugar (SB)	no
Tin	n/a	-	-	only spot and forward prices	no
Unleaded Gas	03.12.1984	HU	NYMEX	missing data in CRB	no
Wheat	01.07.1959	W-	CBOT		yes
Zinc	n/a	-	-	only spot and forward prices	no
				Number of included commodities	**25**

Table 2.3: Monthly Excess Returns of Individual Commodity Futures

Commodity	Geom. Mean	Arith. Mean	t-Stat.	df	p-value	Signif. Code
Canola	-0.55%	-0.36%	-1.0138	300	0.3115	
Cocoa	-0.98%	-0.60%	-1.1724	300	0.2420	
Coffee	-1.36%	-0.75%	-1.1358	300	0.2570	
Copper	0.67%	0.96%	2.1759	300	0.0303	**
Corn	-1.84%	-1.53%	-3.3068	300	0.0011	***
Cotton	-1.05%	-0.69%	-1.4014	300	0.1621	
Crude Oil	0.25%	0.68%	1.2592	300	0.2089	
Feeder Cattle	0.38%	0.46%	2.0482	300	0.0414	**
Gas Oil Petroleum	0.51%	093%	1.7369	300	0.0834	*
Gold	-0.14%	-0.04%	-0.1501	300	0.8808	
Heating Oil	0.44%	0.91%	1.6105	300	0.1083	
Lean Hogs	-1.68%	-1.31%	-2.7250	300	0.0068	***
Live Cattle	0.48%	0.58%	2.2309	300	0.0264	**
Lumber	-2.10%	-1.64%	-2.9640	300	0.0033	***
Oats	1.26%	-0.77%	-1.3254	300	0.1860	
Orange Juice	-1.09%	-0.68%	-1.3095	300	0.1914	
Palladium	0.26%	0.72%	1.2986	300	0.1951	
Platinum	0.37%	0.56%	1.6076	300	0.1090	
Rough Rice	-1.76%	-1.44%	-3.0861	300	0.0022	***
Silver	-0.33%	0.02%	0.0462	300	0.9632	
Soybean Oil	-0.51%	-0.26%	-1.6328	300	0.5274	
Soybeans	0.09%	0.33%	0.8285	300	0.4080	
Soymeal	1.00%	1.33%	2.8099	300	0.0053	***
Sugar	0.27%	0.74%	1.3066	300	0.1923	
Wheat	-1.88%	-1.51%	-3.0578	300	0.0024	***

Significance codes: ***:$p-value < 0.001$; **:$p-value < 0.01$; *:$p-value < 0.05$

In addition to the average monthly returns of the individual commodities, it is interesting to consider an overview of the correlations of the excess returns. As previous research indicates, individual commodities are expected to have very little correlation with each other. Table 2.4 provides the correlations of the individual commodities' monthly excess returns. Most commodities have very little to no correlation ($|p| < 0.5$) with each other. Only four pairs of commodities show a high correlation ($|p| > 0.8$): heating oil and crude oil (0.84), gasoil petroleum and crude oil (0.86), gasoil petroleum and heating oil (0.9) and soymeal and soybeans. This is unsurprising, as three of these pairs are somehow derivatives of the same commodity (crude oil). The last pair (soymeal and soybeans) also seems quite closely related. Further to these strong correlations, there are 12 pairs of commodities that show a moderate correlation ($0.5 < |p| < 0.8$). These commodities are mainly similar types of grains (e.g., wheat/corn), metals (e.g., silver/gold) or animals (e.g., feeder cattle/live cattle). The analysis of the correlations of the individual commodities leads to the confirmation of expectation number two:

Expectation 2

> Individual commodity futures are expected to not yield positive excess returns. The individual commodity futures returns should be rather uncorrelated.

The correlations in this analysis confirm that the selected commodities seem to represent a heterogeneous set of assets that shows a very low correlation between individual commodities. In addition to the individual commodity futures, the price data for the GSCI Excess Return Index was taken from Thomson Reuters Datastream for December 1989–January 2015. As described in the strategies section, the index can be viewed as a trading strategy on its own and will serve as a benchmark for the other strategies. The price data were then used to calculate discrete returns for the GSCI Excess Return Index.

Table 2.4: Monthly Futures Excess Return Correlation Matrix

Commodity	Soyb. Oil	Corn	Cocoa	Crude Oil	Cotton	Feeder Cattle	Gold	Copper	Heat. Oil	Orange Juice	Coffee	Lumber	Live Cattle	Gasoil Pet.	Lean Hogs	Oats	Palla-dium	Plat-inum	Rough Rice	Soy-beans	Sugar	Silver	Soy-meal	Wheat	Canola
Soybean Oil	1.00	0.49	0.16	0.11	0.35	-0.05	0.16	0.27	0.12	0.19	0.14	0.09	0.07	0.10	0.00	0.35	0.08	0.22	0.24	0.73	0.09	0.18	0.43	0.40	0.66
Corn	0.4	1.00	0.18	0.11	0.30	-0.18	0.13	0.12	0.12	0.14	0.19	0.07	-0.01	0.08	0.02	0.47	0.12	0.14	0.31	0.63	0.16	0.20	0.56	0.56	0.46
Cocoa	0.16	0.18	1.00	0.13	0.13	-0.06	0.18	0.17	0.06	0.11	0.15	0.05	-0.06	0.08	0.00	0.23	0.06	0.24	0.14	0.17	0.09	0.23	0.12	0.12	0.10
Crude Oil	0.11	0.11	0.13	1.00	0.08	0.06	0.19	0.28	0.84	0.10	0.05	0.10	0.05	0.86	0.04	0.13	0.16	0.24	0.002	0.13	0.06	0.19	0.08	0.10	0.01
Cotton	0.35	0.30	0.13	0.08	1.00	0.03	0.09	0.26	0.08	0.10	0.13	0.09	0.03	0.08	0.04	0.17	0.17	0.18	0.14	0.30	0.16	0.12	0.18	0.20	0.27
Feeder Cattle	-0.05	-0.18	-0.06	0.06	0.03	1.00	-0.13	0.04	0.07	0.02	-0.01	0.09	0.65	0.10	0.36	-0.11	0.06	0.01	-0.06	-0.08	-0.01	-0.08	-0.07	-0.11	-0.08
Gold	0.16	0.13	0.18	0.19	0.09	-0.13	1.00	0.26	0.15	0.12	0.15	0.02	-0.07	0.19	-0.01	0.15	0.23	0.54	0.03	0.14	0.10	0.71	0.08	0.16	0.03
Copper	0.27	0.12	0.17	0.28	0.26	0.04	0.26	1.00	0.26	0.12	0.16	0.13	0.11	0.26	0.01	0.13	0.24	0.38	0.13	0.19	0.18	0.30	0.10	0.18	0.10
Heating Oil	0.12	0.12	0.06	0.84	0.08	0.07	0.15	0.26	1.00	0.07	0.004	0.06	0.04	0.90	0.06	0.12	0.11	0.21	-0.02	0.17	0.03	0.15	0.13	0.11	0.01
Orange Juice	0.19	0.14	0.11	0.10	0.10	0.02	0.12	0.12	0.07	1.00	0.09	-0.01	-0.03	0.07	0.01	0.13	0.13	0.17	0.04	0.13	0.09	0.12	0.07	0.09	0.11
Coffee	0.14	0.19	0.15	0.05	0.13	-0.01	0.15	0.16	0.004	0.09	1.00	0.08	0.00	-0.01	-0.04	0.19	0.19	0.18	0.02	0.16	0.08	0.20	0.13	0.17	0.06
Lumber	0.09	0.07	0.05	0.10	0.09	0.09	0.02	0.13	0.06	-0.01	0.08	1.00	0.13	0.06	0.09	0.003	0.07	0.08	0.07	0.10	0.07	0.07	0.08	0.15	0.06
Live Cattle	0.07	-0.01	-0.06	0.05	0.03	0.65	-0.07	0.11	0.04	-0.03	0.00	0.13	1.00	0.07	0.33	0.04	0.03	0.02	0.06	0.05	0.02	-0.06	0.04	0.01	-0.01
Gasoil Petroleum	0.10	0.08	0.08	0.86	0.08	0.10	0.19	0.26	0.90	0.07	-0.01	0.06	0.07	1.00	0.07	0.08	0.09	0.21	-0.02	0.16	0.04	0.18	0.12	0.06	0.01
Lean Hogs	0.00	0.02	0.00	0.04	0.04	0.36	-0.01	0.01	0.06	0.01	-0.04	0.09	0.33	0.07	1.00	0.06	-0.04	-0.10	0.04	-0.03	-0.05	-0.02	-0.08	0.11	-0.07
Oats	0.35	0.47	0.23	0.13	0.17	-0.11	0.15	0.13	0.12	0.13	0.19	0.003	0.04	0.08	0.06	1.00	0.10	0.19	0.13	0.44	0.18	0.18	0.39	0.37	0.34
Palladium	0.08	0.12	0.06	0.16	0.17	0.06	0.23	0.24	0.11	0.13	0.19	0.07	0.03	0.09	-0.04	0.10	1.00	0.54	-0.01	0.13	0.15	0.33	0.11	0.12	0.10
Platinum	0.22	0.14	0.24	0.24	0.18	0.01	0.54	0.38	0.21	0.17	0.18	0.08	0.02	0.21	-0.10	0.19	0.54	1.00	0.06	0.20	0.24	0.57	0.13	0.16	0.14
Rough Rice	0.24	0.31	0.14	0.002	0.14	-0.06	0.03	0.13	-0.02	0.04	0.02	0.07	0.06	-0.02	0.04	0.13	-0.01	0.06	1.00	0.28	0.08	0.06	0.20	0.23	0.18
Soybeans	0.73	0.63	0.17	0.13	0.30	-0.08	0.14	0.19	0.17	0.13	0.16	0.10	0.05	0.16	-0.03	0.44	0.13	0.20	0.28	1.00	0.13	0.16	0.88	0.43	0.68
Sugar	0.09	0.16	0.09	0.06	0.16	-0.01	0.10	0.18	0.03	0.09	0.08	0.07	0.02	0.04	-0.05	0.18	0.15	0.24	0.08	0.13	1.00	0.13	0.10	0.15	0.15
Silver	0.18	0.20	0.23	0.19	0.12	-0.08	0.71	0.30	0.15	0.12	0.20	0.07	-0.06	0.18	-0.02	0.18	0.33	0.57	0.06	0.16	0.13	1.00	0.08	0.15	0.12
Soymeal	0.43	0.56	0.12	0.08	0.18	-0.07	0.08	0.10	0.13	0.07	0.13	0.08	0.04	0.12	-0.08	0.39	0.11	0.13	0.20	0.88	0.10	0.08	1.00	0.37	0.52
Wheat	0.40	0.56	0.12	0.10	0.20	-0.11	0.16	0.18	0.11	0.09	0.17	0.15	0.01	0.06	0.11	0.37	0.12	0.16	0.23	0.43	0.15	0.15	0.37	1.00	0.39
Canola	0.66	0.46	0.10	0.01	0.27	-0.08	0.03	0.10	0.01	0.11	0.06	0.06	-0.01	0.01	-0.07	0.34	0.10	0.14	0.18	0.68	0.15	0.12	0.52	0.39	1.00

Risk factors

As well as the commodity futures price data, an extensive dataset was used to analyze the sensitivity of the smart beta commodity futures strategies to different risk factors. In this analysis, a wide range of risk factors should be used, including equity risk factors, bond risk factors and possible commodity-specific risk factors. The dataset encompasses nine risk factors: developed market risk, emerging market risk, size factor, book-to-market equity factor, momentum factor, default premium, term premium, currency risk factor and inflation. Equity- and bond-specific risk factors were included to control for possible risk factor exposures linked to other common asset classes. The same time period was used as for the commodity futures trading strategies for the data on each risk factor (January 1995–January 2015).

Developed Market Risk (DM)

As a proxy for the market risk in developed markets, all stocks traded at the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX) and the National Association of Securities Dealers Automated Quotations (NASDAQ) were used. The aggregated total return data for these stocks was taken from Kenneth French website. The total return includes dividends and adjusts for stock splits. To isolate the market risk premium, the risk-free rate (Treasury bill rate) was subtracted from the total return of the equity portfolio. The returns were calculated as monthly returns (at the end of month) to match the commodity futures trading strategy.

Energing Market Risk (EM)

Recent research shows that commodity markets are also closely linked to the evolution of developing countries. Therefore, economic growth of developing countries is considered a significant driver of commodity prices (Tang and Xiong, 2012). Thus, emerging market risk was added as a risk factor and to distinguish between the developed market risk and the emerging market risk.

To control for the emerging market risk, the MSCI Emerging Markets Index was chosen as a proxy. The MSCI Emerging Markets is a market cap-weighted equity index that represents approximately 85% of the market capitalisation of 24 emerging market countries. Due to its broad coverage of equity markets in developing countries, it is a suitable proxy for the emerging market risk. The total return data for the MSCI Emerging Markets were taken from the Thomson Reuters Datastream. In conformity with the developed market risk, the risk-free rate (Treasury bill rate) was subtracted from the monthly returns of the MSCI Emerging Markets to extract the risk premium.

Size Factor (SMB)

The size factor is motivated by Fama/French. They showed that the market value of equity has significant power in explaining the cross-section of stock returns (Fama and French, 1992). The size effect holds that the size of a company and the returns of the stock are negatively correlated (Fama and French, 1992). A risk-based explanation for this relationship is that smaller firms are riskier than larger companies. Hence, investors demand a premium for smaller companies. The size factor (SMB) is calculated as the difference between the average return of three portfolios of small companies (small value, small neutral and small growth) and three portfolios of big companies (big value, big neutral and big growth). The return data for the size factor were again taken from the Kenneth French website and converted to monthly returns to meet the commodity strategies.

Book-to-Market Factor (HML)

Similar to the size factor, the book-to-market factor also has an explanatory power in the cross-section of stock returns (Fama and French, 1992). The book-to-market factor is based on the relationship of book value of equity to market value of equity (BE/ME). Fama/French reported a positive correlation between the BE/ME-ratio and the average monthly return for stocks (Fama and French, 1992). A possible risk-based explanation for the book-to-market factor is that companies with relatively weak future earnings expectations are traded at a discount and tend to offer higher returns (value companies) (Fama and French, 1992).

The book-to-market factor (HML) is calculated as the difference between the average returns of two portfolios of high BE/ME companies (small value and big value) and two portfolios of low BE/ME companies (small growth and big growth). The return data of the book-to-market factor were also taken from the Kenneth French website and converted to monthly returns.

Momentum Factor (MOM)

As asserted previously, the momentum effect describes the medium-term persistence of stock returns. It is rather difficult to interpret the momentum factor as a risk premium. Nevertheless, the momentum can be a strong driver of stocks returns (Jegadeesh and Titman, 1993). To have a wide range of possible risk factors, it should be included in the analysis.

The data for the momentum factor were also taken from Kenneth French website and converted to monthly returns. The momentum factor was formed by calculating the difference in returns between two portfolios with high prior returns and two portfolios with low prior returns. Each portfolio was preselected based on the firm size. The breakpoint for the high prior returns was the 70th return percentile and for the low prior returns the 30th return percentile of all NYSE-listed stocks.

Term Premium (TERM)

Whereas the previously discussed risk factors are equity-specific risk factors, the term premium is a bond-specific risk factor. The term risk premium can be defined as the difference between long-term bonds and short-term money market instruments. This premium will compensate for the risk of unexpected changes in the interest rate (Chen et al., 1986). Fama/French showed that the term factor is a very useful factor in explaining the returns of high-grade corporate bonds (Fama and French, 1993).

For the measurement of the term premium, the yield spread between 10-year Treasury bonds and the three-month Treasury bills was chosen. The yields were published by the Federal Reserve Bank and the data were taken from Thomson Reuters Datastream.

Default Premium (DEF)

The default premium is the second bond-specific risk factor proposed by Fama/French. They argued that investors demand a risk premium for risky bonds like corporate bonds (Fama and French, 1993). To analyze the risk exposure of commodities to a default premium, the end of month yield spread between AAA-corporate bonds and BBB-corporate bonds was used as a proxy for the default premium. The yields for the AAA- and BBB-corporate bonds were published by Moody's Corporation and the data were taken from Thomson Reuters Datastream.

Currency Risk Factor (USD)

Ferson/Harvey and Dumas/Solnik showed that a risk premium for foreign exchange rate risk can explain securities returns /citepFerson1993. Erb/Harvey also analyzed the risk exposure of commodities to exchange rate risk using the trade-weighted dollar index (Erb and Harvey, 2006). To capture the foreign exchange rate risk, the monthly changes of the trade-weighted dollar index, published by the Federal Reserve Bank, was used in this analysis. According to the Federal Reserve Bank, the trade-weighted dollar index is 'a weighted average of foreign exchange value of the US dollar against currencies of a broad group of major US trading partners'.

Inflation (INF)

Inflation is a possible commodity-specific risk factor that could be used to explain returns of commodity futures portfolio. It can be shown that the inflation rate is positively correlated with commodity indices (Greer, 2000). Inflation can be decomposed into expected inflation and unexpected inflation (Greer, 2000). If inflation is

expected, it should be anticipated by the capital markets; therefore, it cannot be considered a risk factor. Only the unexpected part of the inflation is a risk factor for investors.
A simple measure for unexpected inflation is the change in inflation (Erb and Harvey, 2006). For this analysis, the monthly change in US inflation was chosen as a measure for unexpected inflation to be consistent with the monthly trading strategies. To calculate the monthly change in the inflation rate, the end of month data of the Consumer Price Index (CPI) published by the Federal Reserve Bank was used.

2.5 Empirical Results

Performance and risk analysis
The performance and risk analysis conducted in this section should answer the second aspect of the research question regarding the past performance of smart beta strategies.

2. Which returns were achieved by applying these strategies in the past?

Table 2.5 summarises the annualised performance of the six smart beta strategies and the GSCI Excess Return Index as a benchmark. Figure 2.1 shows the hypothetical growth of a $1 investment in each strategy starting from January 1995 to illustrate the development of each strategy.
For January 1995–January 2015, the term structure strategies were the by far the most profitable strategies. The top quintile strategy generated a geometric average excess return of 23.33% p.a. (standard deviation 19.93%); the relative backwardation strategy even yielded 25.19% p.a. (standard deviation 23.17%). Focusing on the returns, the equal weight strategy was also rather successful, with a geometric average excess return of 5.03% p.a. (standard deviation 16.90%). Compared to the term structure strategies, the momentum strategies performed rather weakly. The momentum quintile strategy only yielded a geometric average excess return of 2.56% p.a. (standard deviation 21.05%) and the relative strength strategy 2.46% p.a. (standard deviation 20.79%). The worst performing strategies were the GSCI Index strategy (–1.17% p.a., standard deviation 22.12%) and the low-volatility strategies (1.82% p.a. and 0.81% p.a.). The impact of the different weighting schemes seems to be limited, as the returns were similar for a given strategy (low volatility, momentum and term structure).
The Sharpe ratios (risk-to-reward ratio) show a very similar picture. Although the risk, measured as standard deviation, is relatively high for the term structure

strategies, the investors are over-compensated for this risk, as the highest Sharpe ratios reveal (1.1706 and 1.0871 respectively). While the equal weight strategy also provided an attractive Sharpe ratio of 0.2978, the index strategy (–0.0528), the low-volatility strategies (0.1770 and 0.0835) and the momentum strategies (0.1215 and 0.1185) were rather unattractive from a risk-and-reward perspective.
Only the equal weight and the two term structure strategies yielded significant positive excess returns (on 10% level and 0.1% level), while the annual arithmetic average excess return of the other strategies was not significantly different from zero. The momentum relative strength (0.3265) and the term structure relative backwardation strategy (0.4600) had slightly positive skewed returns, whereas the other strategies showed a negative skewness in the returns.
After this short summary of the return and risk analysis, the following conclusions can be drawn for the expectations formulated in Section 2.2:

Expectation 1

> All commodity futures smart beta strategies are expected to yield positive excess returns.

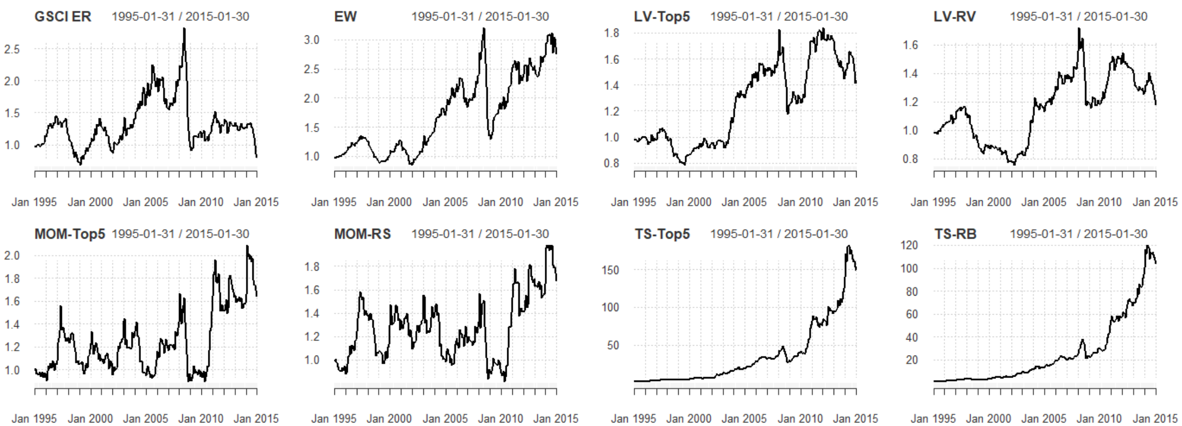
All smart beta strategies provided positive excess returns for investors. However, the positive excess returns were only significant for the equal weight and the term structure strategies. Therefore, it is questionable whether all smart beta strategies can be reliable sources of positive returns.
The low mean excess return of the low volatility strategy was actually rather surprising. On equity markets, the low volatility strategies tends to combine a low volatility with relatively high returns (Baker et al., 2011). The low returns suggest that this may not be the case for commodity futures markets. In other words, there is no low-volatility anomaly in the analyzed commodity futures data. Nevertheless, the low-volatility strategy achieved its main goal of minimising the portfolio variance, as it has the lowest standard deviation of all strategies. It is also quite surprising that the GSCI index strategy was the worst performing strategy. Hence, investors should be careful using index strategies on commodity futures markets, as they are complex trading strategies and not necessarily efficient.
Expectation 2 has already been discussed in the commodity dataset section.

Table 2.5: Annualised Excess Returns and Risk of Smart Beta Strategies (January 1995–January 2015)

Strategy	**Geom. Mean**	**Arith. Mean**	**Std. Dev.**	**t-Stat.**	**Sig.Code**	**Skewness**	**Sharpe-Ratio**
GSCI Excess Return	-1.17%	1.32%	22.12%	0.2682		-0.3604	-0.0528
Equal Weight	5.03%	6.50%	16.90%	1.7237	*	-0.9116	0.2978
Low Volatility Top Quintile	1.82%	2.35%	10.26%	1.0240		-0.3241	0.1770
Low Volatility Relative Volatility	0.81%	1.28%	9.67%	0.5911		-0.1876	0.0835
Momentum Top Quintile	2.56%	4.75%	21.05%	1.0110		0.2522	0.1215
Momentum Relative Strength	2.46%	4.60%	20.79%	0.9908		0.3265	0.1185
Term Structure Top Quintile	23.33%	25.30%	19.93%	5.6883	***	-0.2346	1.1706
Term Structure Relative Backwardation	25.19%	27.77%	23.17%	5.3717	***	0.4600	1.0871

Significance codes: ***:$p-value < 0.001$; **:$p-value < 0.01$; *:$p-value < 0.05$; . : $p-value < 0.1$

Figure 2.1: Hypothetical Growth of $1 Investment (January 1995 to January 2015)



Expectation 3

> Momentum and term structure strategies are expected to yield the highest excess returns.

While momentum and term structure strategies both yielded high excess returns in previous studies, the results in this analysis were split. The momentum strategies with a one-month ranking and a one-month holding period only provided low and insignificant positive excess returns. One possible reason for this poor performance could be the choice of the ranking and holding periods. A different combination might deliver more compelling results. It is also unclear whether the positive returns of momentum strategies were mainly driven by the long positions, short positions or both. The results for the long-only strategy suggest that momentum strategies on commodity markets might not be solely driven by long positions.
Interesting insights are provided by the strong results of the term structure strategies. The signals from the commodity futures term structure seem to contain valuable information for investors, as the term structure strategies outperform all other analyzed trading strategies.

Expectation 4

> Momentum and term structure strategies are expected to have the highest Sharpe ratios.

If returns are adjusted for risk using the Sharpe ratio, the overall picture remains unchanged. Investors are actually overcompensated for their risks when using term structure strategies in comparison to other smart beta strategies. The long-only momentum strategies again could not meet the expectations outlined in the literature. The equal weight strategy also offers a fairly competitive Sharpe ratio. Although the equal weight strategy uses a fairly naive diversification method, it seems to be a very effective strategy for commodity futures markets. It can be deducted that the equal weight strategy is especially effective on commodity markets because it utilises the property of uncorrelated commodities better than many other strategies by simply going long in every contract.
It also would interesting to determine the performance of smart beta strategies for different subperiods. Is it possible that the profits of the momentum and term struc-

ture strategies eroded after they were discovered for commodity markets? Table 2.6 summarises the annualised arithmetic mean returns for five-year subperiods beginning January 1995.

Neither the momentum nor the term structure strategies showed a downward trend

Table 2.6: Annualised Arithmetic Mean Returns for Subperiods

Subperiod	**GSCI ER**	**Equal Weight**	**LV-Top5**	**LV-RV**	**MOM-Top5**	**MOM-RS**	**TS-Top5**	**TS-RB**
01/1995-12/1999	1.01%	0.41%	-2.78%	-2.39%	3.67%	3.89%	24.84%	30.54%
01/2000-12/2004	12.60%	11.83%	8.89%	5.98%	-0.05%	-1.07%	30.87%	33.23%
01/2005-12/2009	-1.79%	5.22%	0.66%	1.44%	1.19%	1.84%	19.35%	18.27%
01/2010-01/2015	-6.39%	8.50%	2.60%	0.08%	14.02%	13.56%	26.18%	29.02%

in the mean average excess return over the last five years. Instead, the last five years were the most profitable of the four subperiods for the momentum strategies (14.02% p.a. and 13.56% p.a. mean excess return). The table also shows the relatively stable returns of the term structure strategies, which ranged from 18.27%p.a. to 33.23% p.a. in the different subperiods for both strategies.

It also shows that the weak performance of the GSCI index strategy was mainly driven by the negative returns in the last 10 years of the analysis (–1.79% p.a. and –6.39% p.a.). It can be presumed that the sharp decline in energy prices combined with the high energy exposure of the GSCI is one possible explanation for the negative returns of the GSCI.

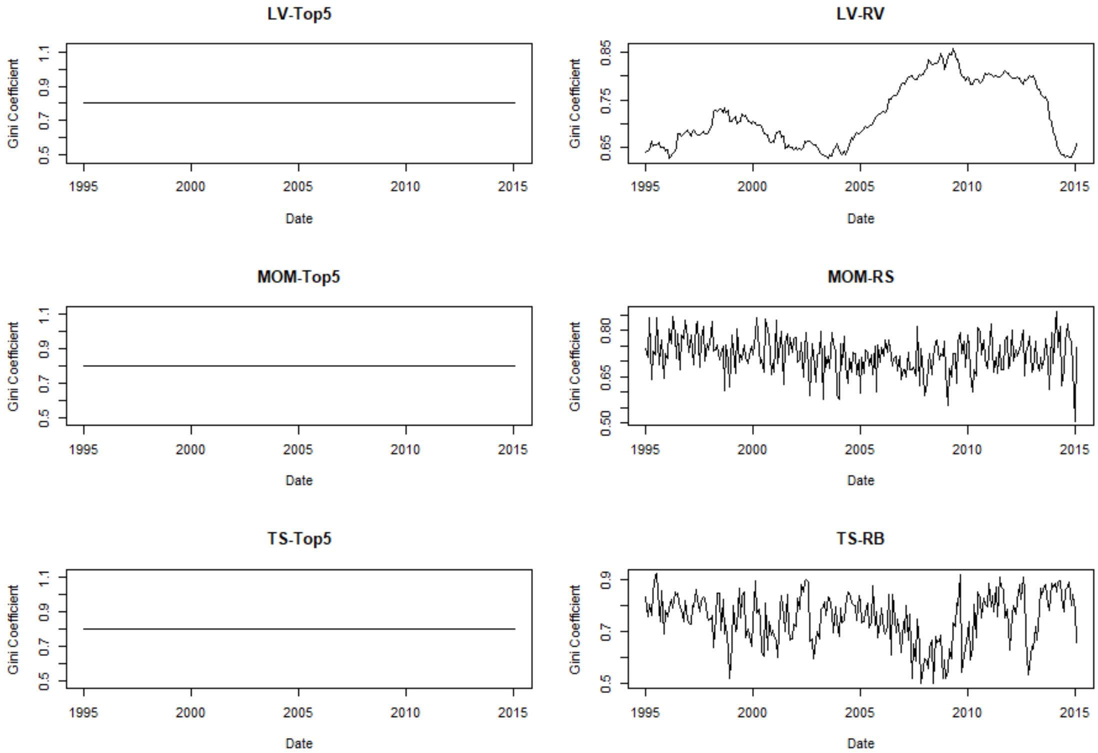
Another interesting property of the smart beta strategies is the concentration of the different strategies. Are the smart beta strategies rather concentrated in single contracts or are they invested in a broader portfolio? Are the relative strength/backwardation strategies more or less concentrated than the top quintile strategies? In other words, can the higher volatility of the relative strength/backwardation strategies be explained by a higher concentration?

To answer these questions, the Gini coefficient for the different strategies was calculated. The Gini coefficient is a concentration measure and expresses the difference between the Lorenz curve of a distribution and the diagonal. For this analysis, the values can range between zero and one for the analyzed portfolio weight, with zero indicating a minimal concentration and one a maximal concentration in one asset.

Figure 2.2 plots the Gini coefficients of each strategy over the time to obtain an impression of the development of the concentration during the analyzed period and Table 2.7 reports the corresponding summary statistics.

The equal weight strategy had a constant Gini coefficient of zero because it distrib-

Figure 2.2: Gini Coefficients for Smart Beta Strategies over Time



utes the portfolio weights equally among all commodities. Similarly, the top quintile strategies that invest equal weight in five out of 25 commodities achieved a constant Gini coefficient of 0.8. The concentration of the relative volatility, relative strength

Table 2.7: Summary Statistics Gini Coefficients

Strategy	**Min**	**Median**	**Mean**	**Max**
Equal Weight	0.00	0.00	0.00	0.00
Low Volatility Top Quintile	0.80	0.80	0.80	0.80
Low Volatility Relative Volatility	0.63	0.70	0.71	0.86
Momentum Top Quintile	0.80	0.80	0.80	0.80
Momentum Relative Strength	0.51	0.72	0.72	0.86
Term Structure Top Quintile	0.80	0.80	0.80	0.80
Term Structure Relative Backwardation	0.50	0.76	0.75	0.92

and relative backwardation strategies is time-dependent and varies between 0.63 and 0.86 for the relative volatility (0.51 and 0.86 for relative strength and between 0.50 and 0.92 for relative backwardation). Median and mean (0.70/0.71 for relative volatility, 0.72/0.72 for relative strength and 0.76/0.75 for relative backwardation) of the relative strategies indicate that the concentration was slightly lower than for the top quintile strategies.

It can be concluded that the higher risk (in terms of standard deviation) for the relative strategies is mainly driven by investments in more volatile commodities than by a higher concentration in these strategies compared to the top quintile strategies. In contrast, the low-volatility strategies achieve their low risk by choosing less-volatile commodities rather than by a low concentration.

Risk Factor Analysis

The third aspect of the research question is to which risk factors the smart beta strategies are exposed and whether they can generate a significant alpha. For this purpose, a multifactor regression was conducted for the monthly excess returns of the smart beta strategies and the GSCI Excess Return Index (Model 2.9). The period for the regression also was January 1995–January 2015. In this non-time dependent model, risk-factor sensitivities are considered static.

$$\begin{aligned} r_{i,t} = \alpha &+ \beta_{EM}(r_{EM,t} - r_{f,t}) + \beta_{DM}(r_{DM,t} - r_{f,t}) + \beta_{SMB} r_{SMB,t} + \beta_{HML} r_{HML,t} \\ &+ \beta_{MOM} r_{MOM,t} + \beta_{USD} r_{USD,t} + \beta_{DEF} r_{DEF,t} + \beta_{TERM} r_{TERM,t} + \beta_{INF} r_{INF,t} + \epsilon_{i,t} \end{aligned} \tag{2.9}$$

The results of the ordinary least squares regression are presented in Table 2.8. To consider possible autocorrelation and heteroskedasticity, Newey-West corrected standard errors with 10 lags were used. According to the results, only the relative backwardation strategy can provide significant positive risk-adjusted excess returns (on 10% significance level). All other strategies also yield positive risk-adjusted excess returns in this model, but these are not significant.

With few exceptions, the bond and equity risk factors are not significant for the returns of the commodity futures strategies. The exceptions are the size factor and momentum factor for GSCI Excess Return Index (10% significance level). Unfortunately, these exposures seem rather random and it cannot be confirmed that there is an economic rationale to argue why the index strategy is particularly exposed to the size and momentum factor.

The commodity-specific risk factors provide some interesting insights into the commodity futures markets. All strategies have a significant negative exposure to the strength of the US dollar (0.1% or 1% significance level). In other words, an appreciating US dollar significantly reduces the excess returns of all smart beta commodity futures portfolios. Consistent with a strand in recent literature, it seems that currency risk is also an economically meaningful risk factor for commodity futures. An appreciating dollar results in rising commodity prices for foreign investors or foreign consumers of commodities. The rising prices for foreign consumers reduce the demand and cause commodity prices to decline on a US dollar basis (Tang and Xiong, 2012).

Another finding in terms of the commodity-specific risk factors is the significant influence of unexpected inflation on the returns of the GSCI, the equal weight strategy (0.1% significance level) and the term structure strategies (1% and 10% significance level). If the inflation rate increases by one percentage point (month-to-month), the return of the GSCI increases c.p. on average by 3.65 percentage points (2.77 percentage points for the equal weight strategy, 1.63 percentage points for the term structure top quintile strategy and 1.38 percentage points for the relative backwardation strategy). These findings identify the index strategy and the equal weight strategy as excellent hedges for unexpected inflation.

So why are the other strategies not a good hedge for unexpected inflation? It can be theorised that the index strategy and the equal weight strategy provide the best inflation hedge because these strategies invest in a very broad selection of commodity futures; other smart beta strategies are far more selective. This hypothesis is also supported by the analysis of the Gini coefficients, which show the minimum concentration for the equal weight strategy. If unexpected inflation occurs, it may only occur within the markets of some commodities. If the commodities affected by unexpected inflation are not in the portfolio of one of the more concentrated smart beta strategies, the inflation hedge might be ineffective.

Expectation 5

> Known risk factors from equity and bond markets cannot explain the returns of smart beta commodity strategies. Inflation risk and currency risk are expected to be a commodity-specific risk factor.

After analysis of the multifactor model, the expectations for the risk factor exposures of smart beta commodity futures strategies can be generally confirmed. With very few minor exceptions, equity and bond risk factors do not seem to explain the returns of the commodity futures strategies. Commodity strategies with a low concentration (index strategies and equal weight) are a highly effective hedge against unexpected inflation. Another significant risk factor is the currency risk of the US dollar. An appreciating US dollar significantly decreases the average returns of all analyzed commodity futures strategies.

Table 2.8: Multifactor Regression Results

Factor	**GSCI ER**	**Equal Weight**	**LV-Top5**	**LV-RV**	**MOM-Top5**	**MOM-RS**	**TS-Top5**	**TS-RB**
alpha	-0.0010	-0.0018	0.0008	0.0018	-0.0001	0.0047	0.0144	**0.0179**
	(-0.0904)	(-0.2551)	(0.1966)	(0.4337)	(-0.0103)	(0.5485)	(1.5877)	(1.9270).
EM	-0.3219	-0.0807	-0.2057	-0.083	0.0056	-0.1353	0.4180	0.2924
	(-0.7935)	(-0.2099)	(-1.0461)	(-0.4435)	(0.0130)	(-0.4187)	(1.1678)	(0.9790)
DM	0.5446	0.2991	0.2134	0.1211	0.1833	0.2373	-0.2476	-0.1593
	(1.3059)	(0.7816)	(1.1872)	(0.6620)	(0.4047)	(0.7038)	(-0.7296)	(-0.5085)
SMB	0.0872	0.1255	-0.0563	-0.0229	0.1810	0.1686	0.1573	0.0171
	(0.7677)	(1.2734)	(-1.0062)	(-0.4189)	(0.9454)	(1.1345)	(1.4092)	(1.5929)
HML	**0.1708**	0.0498	0.0075	0.0031	-0.1538	-0.0889	-0.1042	-0.0998
	(2.1323)*	(0.5099)	(-0.1003)	(0.0549)	(-1.2687)	(-0.8413)	(-0.9868)	(-0.8410)
MOM	**0.1626**	0.0560	-0.0212	-0.0133	0.0906	0.0390	0.0832	0.0577
	(2.0384)*	(0.9590)	(-0.4482)	(-0.4030)	(1.1867)	(0.5615)	(1.2634)	(0.8172)
USD	**-1.0576**	**-0.7393**	**-0.3994**	**-0.5130**	**-0.7704**	**-0.9579**	**-0.7263**	**-0.7854**
	(-5.1637)***	(-3.9896)***	(-3.3753)***	(-4.3781)***	(-3.1023)**	(-4.0287)***	(-3.1137)**	(-2.6804)**
DEF	0.0004	0.0017	-0.0014	-0.0040	0.0057	-0.0006	0.0014	-0.0030
	(0.0531)	(0.2396)	(-0.2540)	(-1.1081)	(0.7456)	(-0.0745)	(0.1970)	(-0.3773)
TERM	-0.0003	0.0023	0.0016	0.0018	-0.0017	-0.0005	0.0024	0.0043
	(-0.1083)	(1.0838)	(0.8944)	(1.0964)	(-0.5177)	(-0.1669)	(0.7166)	(1.0284)
INF	**3.6511**	**2.7698**	0.5492	0.1897	0.2593	0.2913	**1.6245**	**1.3837**
	(4.8131)***	(4.2556)***	(1.3663)	(0.5999)	(0.4527)	(0.4618)	(2.4346)*	(1.6585).

T-statistics are stated in parentheses. Sig. codes: ***:$p - value < 0.001$; **:$p - value < 0.01$; *:$p - value < 0.05$; . : $p - value < 0.1$

2.6 Conclusion

The aim of this study was to define smart beta strategies for commodity futures markets and analyze the risk and return profile of these strategies. The first aspect of the research question considers the smart beta strategies that can be defined for commodity futures. It is difficult to clearly define smart beta strategies for commodity markets because there is no market portfolio for commodity futures. For the purpose of this study, smart beta strategies on commodity markets were defined as all trading strategies that use a certain weighting principle that offers a reasonable possibility to generate an attractive risk to return profile; this is done by exploiting an anomaly or using portfolio optimisation techniques. The analysis in this study encompassed seven long-only smart beta strategies: an equal weight strategy, two low volatility strategy, two momentum strategies and two term structure strategies. All of these strategies are simple to implement, as they only need reliable price data for the two nearest futures contracts.

The second aspect of the research question is concerned with the past returns that have been achieved by these smart beta strategies. The empirical analysis used a dataset of 25 commodities for December 1989–January 2015 and the strategies were implemented using the second–nearest contracts. All smart beta strategies yielded positive mean excess returns. However, only the term structure strategies and the equal weight strategy provided significant positive returns. Hence, it remains questionable whether all smart beta strategies are a reliable source of excess returns for investors.

The term structure strategies stand out as the most profitable strategies (excess return of up to 25% p.a.) and providing the highest Sharpe ratio for investors (up to 1.17). The results of these strategies are also stable across different five-year subperiods, making it an interesting investment case. The results suggest that the signals from term structure are of great value for investors.

The last aspect of the research question is concerned with the risk factor exposure of the smart beta strategies. Smart beta commodity strategies are unlikely to be sensitive to known equity or bond risk factors. Indeed, they are sensitive to the strength of the US dollar and the well-diversified strategies (the equal weight and index strategies) are also a good hedge against unexpected inflation.

Overall, the analysis results align with the expectations drawn from the existing literature on commodity futures trading strategies. The hedging pressure theory provides a possible explanation for the high returns of the term structure strategies.

If the demand for short hedging exceeds the long interest of investors and speculators for one commodity, the futures prices will have to decrease to induce additional long interest. The decrease in commodity futures prices will result in a backwardated futures term structure, which provides an insurance premium for investors. The term structure strategies then select the contracts with the highest insurance premium by using the backwardation to determine the portfolio weights. In other words, the term structure strategies invest in commodity futures with the highest imbalance between short hedging demand and investors' or speculators' interests to supply the hedging demand. However, it is questionable whether this strategy could continue to be a reliable source of return to investors. If many commodity futures investors only focus on the backwardation of the commodity futures contracts, this would reduce the backwardation by inducing more long interest, and future excess returns would erode.

Currently, there are two important directions for future research. First, this analysis excluded transaction costs and only used the nearest and second-nearest contracts for investment strategies. Thus, an expansion of the analysis—including transaction costs and more contracts—seems like a natural next step for future research. Possibly, the already insignificant excess returns of, for example, the long-only momentum strategies would even be closer to zero after accounting for transactions costs.

Second, the pricing mechanisms of the commodity futures markets are still not entirely understood. Which factors influence the determination of commodity futures prices? Further, might there be risk factors or risk premiums that have not yet been considered?

2.7 Appendix

Table 2.9: Overview of selected Commodity Futures Research Studies

Authors	Journal	Year	Analyzed Strategies	Dataset	Datasources	Period
Bodie/Rosansky	Financial Analysts Journal	1980	Equal Weight/Average	23 commodities	Journal of Commerce	12/1949-12/1976
Fama/French	Journal of Business	1987	Equal Weight/Average	22 commodities	CBT/CME etc.	03/1966-07/1984
Greer	The Journal of Alternative Investments	2000	Index Weight (CPCI)	18 commodities	CPCI	1970–1999
Erb/Harvey	Financial Analysts Journal	2006	Equal Weight, Momentum and Term Structure	12 commodities	CRB	07/1959-12/2004
Gorton/Rouwenhorst	Financial Analysts Journal	2006	Equal Weight	36 commodities	CRB	07/1959–12/2004
Miffre/Rallis	Journal of Banking & Finance	2007	Momentum	31 commodities	Datastream	01/1979-09/2004
Fuertes/Miffre/Rallis	Journal of Banking & Finance	2010	Momentum, Term Structure	37 commodities	Datastream, Bloomberg	01/1979-01/2007

Table 2.10: Overview of Previous Commodity Futures Trading Strategy Results

Authors	**Strategies**	**Period**	**Return Type**	**Mean Type**	**Mean Return**	**Std.Dev.**	**Sharpe-Ratio**
Bodie/Rosansky	Equal Weight	12/1949-12/1979	Excess Return	arithmetic	9.77%	21,39%	0.4568
Fama/French	Equal Weight	03/1966-07/1984	Excess Return	geometric	5.54%	14.55%	0.3805
Greer	Index Weight (CPCI)	1970-1999	Total Return	n/a	12.20%	n/a	n/a
Erb/Harvey	Equal Weight (buy-and-hold)	12/1982-05/2004	Excess Return	geometric	0.70%	10.61%	0.0660
Erb/Harvey	Equal Weight (monthly rebalancing)	12/1982-05/2004	Excess Return	geometric	1.01%	10.05%	0.1005
Erb/Harvey	Momentum (long-only)	12/1982-05/2004	Excess Return	geometric	7.00%	n/a	0.5500
Erb/Harvey	Term-Structure	12/1982-05/2004	Excess Return	geometric	3.65%	7.79%	0.4685
Gorton/Rouwenhorst	Equal Weight (monthly rebalancing)	07/1959-12/2004	Excess Return	arithmetic	5.23%	12.10%	0.4322
Miffre/Rallis	Momentum (long-only)	01/1979-09/2004	Excess Return	geometric	2.39%	20.16%	0.1186
Fuertes/Miffre/Rallis	Momentum (long-only)	01/1979-01/2007	Excess Return	geometric	12.39%	10.61%	1.1678
Fuertes/Miffre/Rallis	Term Structure (long-only)	01/1979-01/2007	Excess Return	geometric	8.49%	6.97%	1.2181

3 A Factor Decomposition of Term Premiums in Commodity Futures Markets

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Abstract

This study examines the term structure of expected commodity futures returns using a factor decomposition implied by pricing models. A three-factor model leads to a decomposition of term premiums into a constant, a linear function, and a convex function of the time to maturity. In an empirical study for eight commodities, we show that term premiums for maturities between one and twelve months are well explained by this three-factor model. Moreover, the slope and curvature of the model-based term structure of expected futures returns provide informative signals for profitable trading strategies that achieve Sharpe ratios up to 0.93.

JEL Classification: G12, G13
Keywords: commodity futures; expected returns; term premiums; factor models

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3.1 Introduction

The understanding of expected returns of commodity futures is a prerequisite for the design of successful investment and hedging strategies. However, there is a specific challenge to the design of such strategies in commodity markets. Because futures contracts with different maturities exist simultaneously, investors and hedgers can choose among instruments that are closely linked economically. Therefore, a full understanding of expected returns requires an understanding of the entire term structure of expected returns, i.e., all term premiums. This is not an easy task, because expected returns are unobservable and estimates are hampered by noisy historical returns and the difficulty to find appropriate conditioning variables.

In this paper, we use pricing models for commodity futures to gain new insights into term premiums in commodity futures markets. We suggest that the N-factor model originally proposed by Cortazar and Naranjo (2006) offers an adequate framework to investigate the factor structure of such premiums. We show that a three-factor variant of the model delivers a simple decomposition of expected futures returns into a constant, a term that is linear in the time to maturity of the futures contracts and a nonlinear term. Moreover, the decomposition is arbitrage-free due to the no-arbitrage restrictions implied by the valuation model, does not depend on unobserved state variables and allows for a straightforward estimation of the remaining model parameters. In an empirical study for eight commodities belonging to the groups of energy, metals and grains, we find that our proposed three-factor model provides a very good description of the term structure of expected commodity futures returns. Moreover, the model delivers informative signals about realized futures returns over the next month for metals and grains. Using signals on the level, the slope and the curvature of the term structure of expected futures returns, strategies based on slope and curvature signals deliver significant excess mean returns of up to 8.7% p.a. and Sharpe ratios of up to 0.93.

The theoretical basis of our work relates to Cortazar et al. (2015) who point out that many valuation models for commodity futures also provide a characterization of expected returns. Such models describe the log spot price of a commodity as a weighted sum of latent stochastic factors. The first model of this type is the one-factor model of Schwartz (1997). Schwartz and Smith (2000) extend the one-factor model to the well-known short-term-long-term two-factor model with one nonstationary and one stationary factor. Sørensen (2002) adds a deterministic seasonal component to the short-term-long-term model, Korn (2005) provides further flexibility by allowing both factors to be stationary, and Cortazar and Naranjo (2006) develop an N-factor model with one nonstationary and $N-1$ stationary factors.[1] Our analysis exploits the flexibility of the N-factor model and shows that a three-factor version of this model class provides an intuitive characterization of the term structure of expected futures returns as a combination of a constant, a linear term and a nonlinear term.

Our work is also inspired by some analogies to the literature on bond returns and yield curve modeling. Litterman and Scheinkman (1991) show that expected bond returns can be well explained by three attributes (or factors) of the yield curve, which they call “level”, “steepness” and “curvature”. This is analogous to the factor interpretation of the three-factor model that we use. Moreover, our approach shares the idea of a parsimonious yet flexible modeling of a “term structure” with the yield curve models by Nelson and Siegel (1987) and Svensson (1994). As shown by Diebold and Li (2006), the three parameters of Nelson's and Siegel's model can also be interpreted as “level”, “slope” and “curvature”. Interestingly, the question whether such models are arbitrage-free is an important aspect of this literature (Coroneo et al., 2008; Christensen et al., 2009). Our paper already starts from an arbitrage-free model, which is then shown to provide parsimonious yet flexible characterizations of the term structure of expected returns.

Our work makes several contributions to the literature. First, it provides a deeper understanding of valuation models for commodity derivatives and their suitability in various contexts. Valuation models may work well for certain tasks, for example, explaining the futures curve or the volatility curve. However, providing a sensible description of expected returns is important too; and very little is known about the performance of valuation models in this dimension. One notable exception is the observation by Cortazar et al. (2015) that the two-factor model of Schwartz and Smith (2000) does not lead to reasonable predictions of the expected returns of long-term contracts for copper and oil. As a remedy, they suggest to use additional restrictions on the model parameters based on the CAPM. Alternatively, Cortazar et al. (2019) suggest to improve model-implied estimates of long-term expected futures returns for oil by augmenting historical futures prices with analyst forecasts. In contrast to these papers, our study focuses on shorter maturities between one and twelve months. Shorter-maturity contracts are very important for commodity investing and hedging and attract most of the trading volume. We study eight

[1] Casassus and Collin-Dufresne (2005) show how this type of model can be combined with models that use a stochastic convenience yield, such as the model by Gibson and Schwartz (1990).

different commodities and ask for the required model complexity to achieve a good description of term premiums within the one-year maturity range. In addition, we test the informativeness of the fitted expected return curves via different trading strategies.

Second, the paper contributes to a better understanding of the driving forces of commodity futures markets by looking at the factor structure of term premiums. Several studies investigate the factor structure of commodity futures returns (e.g., Bessembinder and Chan, 1992; Daskalaki et al., 2014; Bakshi et al., 2019; Christoffersen et al., 2019; Kang et al., 2020). However, all of these studies concentrate on the cross section of different commodities, i.e., they do not investigate term premiums. A notable exception is Szymanowska et al. (2014). This study uses a cost-of-carry model to decompose the overall premium of futures contracts into a spot premium and a term premium. However, the term premium itself is not further decomposed or attributed to different factors. In contrast, our study looks at the factor structure of term premiums implied by the N-factor model of Cortazar and Naranjo (2006).

Finally, our paper contributes to the literature on trading strategies with commodity futures. Miffre (2016) provides an excellent review of this literature, with a specific focus on long-short strategies. The trading strategies that we use to test the informativeness of the expected return curves belong to the category of "curve strategies". A curve strategy simultaneously takes positions in futures contracts with different maturities or uses information from the futures curve to set up a position. Different curve strategies have been investigated in the literature (Mouakhar and Roberge, 2010; DeGroot et al., 2014; Szymanowska et al., 2014; Paschke et al., 2020). The novel feature of our work is that the signals do not come from the futures curve or its dynamics alone, but are based on the model-implied expected return curve. In particular, the corresponding slope and curvature strategies—which are long-short strategies—can deliver high returns and high Sharpe ratios.

The remainder of the paper is organized as follows. Section 2 describes the theoretical framework and illustrates the relationship between the multi-factor commodity pricing model by Cortazar and Naranjo (2006) and the term structure of expected futures returns. Section 3 provides a description of the data on commodity futures prices applied in this study, while Section 4 examines how well the suggested factor models capture the structure of empirical futures returns. Section 5 applies different trading strategies based on signals derived from the estimated factor models and investigates the performance of these strategies. Section 6 concludes.

3.2 The Factor Structure of Expected Returns

The starting point of our analysis is the N-factor model of commodity futures prices by Cortazar and Naranjo (2006). This model is an N-factor extension of the popular short-term-long-term model by Schwartz and Smith (2000). It describes the log commodity price as the sum of N latent, potentially correlated factors.[2] The factor dynamics of the first factor (Factor 1) follow a Brownian motion, whereas the dynamics of the remaining factors (Factors 2 to N) follow Ornstein-Uhlenbeck processes. The economic intuition behind the model is that some permanent changes in commodity prices—captured by Factor 1—are superimposed by some temporary changes due to $N-1$ additional sources of risk—captured by Factors 2 to N.

Denote by $F_{t,T}$ and $F_{t+h,T}$ the futures prices at times t and $t+h$, respectively, of a futures contract expiring at time T. From the perspective of time t, the price $F_{t+h,T}$ is a random variable, as is the gross return $F_{t+h,T}/F_{t,T}$ for the holding period of length h.[3] As shown in Appendix 3.7.1, under the N-factor model by Cortazar and Naranjo (2006), the expected gross return under the physical measure equals

$$E_t\left(\frac{F_{t+h,T}}{F_{t,T}}\right) = \exp\left(\lambda_1 \cdot h + \sum_{i=2}^{N} \lambda_i \cdot g(\kappa_i, T-t, h)\right), \qquad (3.1)$$

with model parameters $\lambda_1, \ldots, \lambda_N$ and $\kappa_2 > 0, \ldots, \kappa_N > 0$. The λs are the market prices of risk of the respective factors, and the κs are the mean-reversion parameters of the $N-1$ stationary factors. The functions $g(\kappa_i, T-t, h)$ are defined as

$$g(\kappa_i, T-t, h) \equiv \frac{\exp\left(-\kappa_i \cdot (T-t-h)\right) - \exp\left(-\kappa_i \cdot (T-t)\right)}{\kappa_i}, \ i = 2, \ldots, N. \qquad (3.2)$$

Equation (3.1) delivers a model-implied characterization of the term premiums. It shows a functional relation between the time to maturity $(T-t)$ of a futures contract and its expected gross return over a holding period h, i.e., the term structure of expected futures returns. Because T can take any value between $t+h$ and infinity, Equation (3.1) provides a mapping of an infinite-dimensional object on a finite set

[2] One could easily add a deterministic seasonal component, as in Sørensen (2002), to obtain a more adequate description of the price dynamics for some commodities. However, a deterministic seasonal component does not affect model-implied expected futures returns, which are the focus of this study.

[3] The return of a futures contract is not a straightforward concept, because futures do not require an initial investment. The simple return $F_{t+h,T}/F_{t,T} - 1$ can be interpreted as the excess return over the risk-free rate of the following strategy: Buy one futures contract and fully collateralize it by investing the amount $F_{t,T}$ in a risk-free asset.

of parameters (λs and κs). This reduction in complexity has potential advantages in terms of economic interpretation and application. One of the main questions of this paper is how restrictive or flexible the model needs to be for an adequate description of the term structure of expected futures returns. This question boils down to the question of how many factors to use for specific commodities.

Taking logarithms on both sides of Equation (3.1) leads to an alternative characterization of the term structure of expected futures returns, as shown in Equation (3.3). The log expected gross return of a futures contract with maturity date T is just a linear function of the expressions $g(\kappa_i, T-t, h)$, with coefficients equal to the corresponding market prices of risk.[4] This simple linear structure provides an intuitive visualization of how different model specifications translate into different term structures; and we will use it in Section 3.4.

$$\ln\left[E_t\left(\frac{F_{t+h,T}}{F_{t,T}}\right)\right] = \lambda_1 \cdot h + \sum_{i=2}^{N} \lambda_i \cdot g(\kappa_i, T-t, h). \tag{3.3}$$

To dig deeper into the interpretation of the term structure of expected futures returns, we look at yet another characterization. Equation (3.4) presents annualized expected simple returns.

$$\frac{E_t\left(\frac{F_{t+h,T}}{F_{t,T}}\right) - 1}{h} = \frac{\exp\left(\lambda_1 \cdot h + \sum_{i=2}^{N} \lambda_i \cdot g(\kappa_i, T-t, h)\right) - 1}{h}. \tag{3.4}$$

Equation (3.4) highlights several important features of the term structure of expected futures returns: First, expected futures returns neither depend on the variances and co-variances of the stochastic factors nor on the drift rate of the first factor. This property implies that a model-based analysis of term premiums can concentrate on a subset of model parameters. For example, for a three-factor variant of the model, the total number of model parameters is twelve, whereas the subset of parameters relevant for the analysis of the term premiums contains only five parameters (κs and λs). Second, expected futures returns also do not depend on the unobserved factors (state variables), in contrast to the futures prices themselves. Therefore, no estimation of state variables is required for the analysis of expected futures returns. Third, if all λs are zero, the expected futures return is zero for all maturities. This is very intuitive, since with zero market prices of risk the expected return of a financial instrument that does not require any initial capital should be zero.

[4] Factor 1 is no exception, because the function $g(\kappa_i, T-t, h)$ converges to h for $\kappa_i \to 0$, i.e., the Ornstein-Uhlenbeck process converges to the Brownian motion.

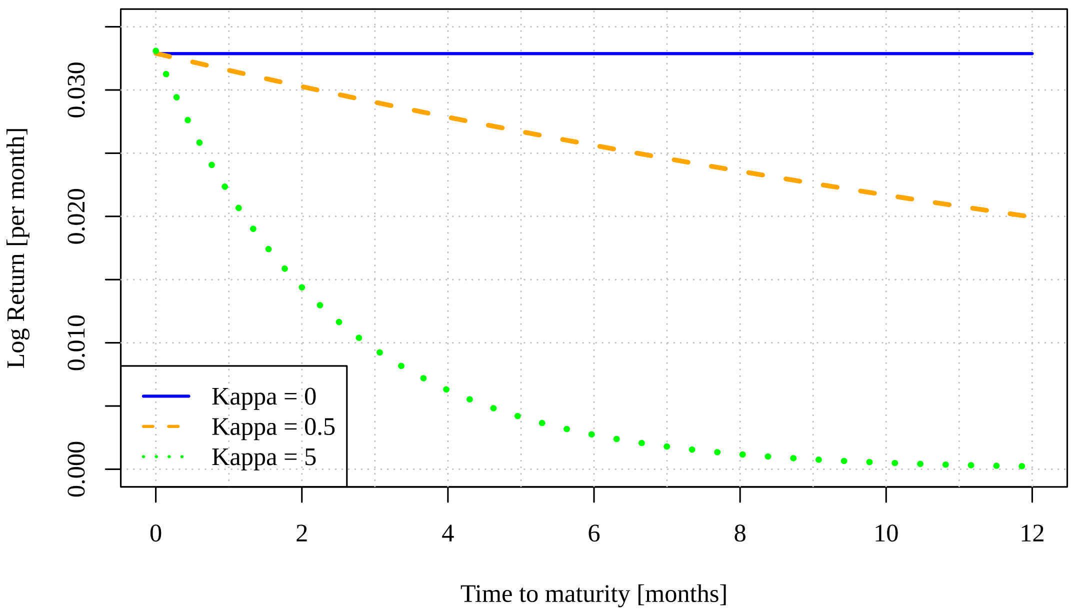
Finally, the lambda parameters have an interpretation in terms of annualized simple returns of specific contracts or portfolios. Consider a futures contract with T going to infinity and a holding period h going to zero. As is shown in Appendix 3.7.2, the annualized simple return of such a contract converges to λ_1. The intuition behind this result is as follows: Factor 1 describes the movement of the long-term commodity price level, and very long-term contracts are essentially exposed to this risk factor only. Therefore, the annualized short-term return of long-term contracts equals the corresponding market price of risk. Consider another case: a very short-term contract with maturity date $t + h$ and a holding period h going to zero. The annualized return of such a contract converges to $\sum_{i=1}^{N} \lambda_i$, as is also shown in Appendix 3.7.2. It follows that $-\sum_{i=2}^{N} \lambda_i$ is the annualized return difference between a (very) long-term and a (very) short-term contract for a (very) short holding period.

These observations are interesting, because they show how certain model parameters provide information on the expected returns of certain futures contracts. However, they just refer to specific limiting cases. What about futures returns of contracts with intermediate maturities over longer holding periods? Does the N-factor valuation model still lead to a simple characterization and interpretation of their term premiums? To answer these questions, we take a closer look at the function g and its dependence on the kappa parameter.

The N-factor model characterizes the i-th factor via the parameters λ_i and κ_i, however, the function g itself is the same for all factors. Due to this property, the model is not globally identified, i.e., its parameters can not be uniquely determined from empirical data. For example, if we just switched all parameters between Factors 2 and 3, we would end up with exactly the same data fit. Essentially, the problem arises because different factors are just latent variables with the same general specification—an Ornstein-Uhlenbeck process; and any distinction between factors results from potentially different parameter values. Factor 1, the long-term factor, is no exception. Its specific form arises from the choice of a mean-reversion parameter "κ_1" of zero. As such, identification of the first factor is achieved by fixing its kappa parameter. Moreover, the specific choice of "κ_1" does not only solve the identification problem, it also leads to an intuitive economic interpretation.

We will now use the same idea for the "identification" of other factors. With the intent to find kappas that deliver simple factor interpretations for the term structure of expected futures returns, we take a closer look at the function g. Figure 3.1 shows g for three different values of kappa (0, 0.5, 5). The x-axis depicts the time

Figure 3.1: Functions g for Different Parameter Values of Kappa



Note: This figure depicts g-functions, as defined in Equation (3.2), for different values of κ. The x-axis shows the time to maturity of a futures contract in months and the y-axis provides the value of the g-function. The holding period h equals one day. The solid line shows the g-function for $\kappa = 0$, the dotted line for $\kappa = 0.5$, and the dashed line for $\kappa = 5$.

to maturity of futures contracts in months, ranging from one to twelve, as in our empirical study. The holding period h is set to one day. The functions in Figure 3.1, multiplied by a corresponding market price of risk, can be interpreted as the contribution of a factor to the expected returns of futures contracts with various times to maturity. For $\kappa = 0$, i.e., the specification of Factor 1, the function g is flat and the contribution of the factor is the same for all maturities. Depending on the sign of the market price of risk, this contribution can be either positive or negative. For $\kappa = 0.5$, the function g comes very close to a linear function. If the corresponding lambda is positive, the resulting factor contribution has a negative slope, i.e., it linearly decreases with the futures' time to maturity. For a negative lambda, the slope is positive. Finally, for $\kappa = 5$, we obtain a clearly non-linear function. If the corresponding lambda is positive, the contribution of the factor is convex in the time to maturity. With a negative lambda, however, the factor contribution is a concave function. Taken together, the functions from Figure 3.1 deliver a simple and intuitive three-factor specification of term premiums: if the identification problem of the valuation model is solved by setting the kappa parameters to 0, 0.5, and 5, respectively, the term premiums of futures are just a weighted sum of a constant, an (almost) linear term and a non-linear term. The importance of each term hinges on the corresponding market prices of risk, which can be determined empirically from futures prices.[5]

In summary, the model by Cortazar and Naranjo (2006) delivers a simple yet flexible arbitrage-free characterization of the term structure of expected futures returns. A three-factor variant of the model with appropriate specifications of kappa parameters delivers a decomposition of term premiums into a constant, a linear term and a non-linear term. This model-based factor decomposition allows for empirical tests of the appropriate factor structure for different commodities and provides the basis for the design of trading strategies that aim to earn term premiums.

3.3 The Data

Our data set consists of futures prices for eight major commodity markets. The commodities belong to the three groups energy, metals and grains. In particular, they cover crude oil, natural gas, gold, silver, copper, wheat, corn, and soybean. The data was sourced from the Commodity Research Bureau's (CRB) Infotech Database, and contracts were selected based on being the benchmark contracts for a particular commodity. Prices are quoted in US Dollar (USD) cents per unit of each commodity: USD cents per barrels for crude oil, USD cents per million British thermal units (mmBtu) for natural gas, USD cents per troy ounce for gold and silver, USD cents per pound for copper and USD cents per bushel for all three grains. The main sample period is January 1975 to January 2019. Note that futures on crude oil, natural gas and copper only started trading after 1975, leading to shorter sample periods for these commodities. The corresponding start dates are July 1986, January 1992 and January 1990, respectively.

We record the closing prices for futures contracts with a remaining time to maturity of up to twelve months on all days when an expiring contract is traded for the last

[5] The specific choices of κ_2 and κ_3 are not crucial for the empirical application of the model, provided that κ_2 is small enough to produce a "linear" function and κ_3 is big enough to produce a "convex" function over the relevant maturity range. For example, if κ_2 is below 0.5, the "linear factor" has a less negative slope. However, this effect would be offset via a higher λ_2 estimate, delivering an almost identical fit to the data and identical trading signals.

time. We choose the last trading days of expiring contracts because on these days the time to maturity of non-expiring contracts is close to one month, two months, three months, and so on. The last trading day within a month usually falls on different days for each commodity. For energy and metals, each month of the data period contributes an observation. However, for grains, not every month is an expiration month, which reduces the number of observations accordingly. To analyze term premiums, we calculate monthly futures returns for all available maturities. For grains, gold and silver, contracts with certain maturities are not available in some months because of the issuance calendar. As a result, the futures return curves consist of different maturities each month, making it difficult to compare these curves over time. In addition, the missing contracts complicate the development of trading strategies which aim to exploit term premiums, a topic we explore in Section 3.5. To obtain a balanced panel data set for each commodity, we impute the prices for missing maturities using linear interpolation, using the prices of the two adjacent contracts. The imputed prices can be used in trading strategies because they refer to tradable portfolios of futures contracts. However, we do not use any form of price extrapolation. Therefore, in the balanced panels, the maximum time to maturity is eleven months for metals and soybean and ten months for wheat and corn.

Table 3.1: Monthly Futures Returns: Data Overview

	Energy						**Metals**									**Grains**								
Commodity	Oil			Gas			Gold			Silver			Copper			Wheat			Corn			Soybean		
Start date	22.07.1986			28.01.1992			28.01.1975			28.01.1975			26.01.1990			14.02.1975			14.02.1975			14.02.1975		
End date	29.01.2019			29.01.2019			29.01.2019			29.01.2019			29.01.2019			14.12.2018			14.12.2018			14.01.2019		
T-t	obs.	μ	σ	obs.	μ	σ	obs.	μ	σ	obs.	μ	σ	obs.	μ	σ	obs.	μ	σ	obs.	μ	σ	obs.	μ	σ
1	390	0.95%	10.33%	324	0.23%	16.16%	528	0.55%	5.54%	528	0.56%	9.55%	346	0.99%	7.55%	220	0.19%	8.35%	220	-0.39%	6.51%	308	0.87%	7.09%
2	390	0.91%	9.53%	324	-0.36%	13.33%	528	0.19%	5.52%	528	0.28%	9.54%	346	0.64%	7.32%	220	-0.15%	7.84%	220	-0.69%	6.53%	308	0.48%	6.86%
3	390	0.93%	9.08%	324	-0.09%	11.75%	528	0.11%	5.41%	528	0.17%	9.43%	346	0.67%	7.24%	220	-0.49%	7.58%	220	-1.00%	6.75%	308	0.16%	6.91%
4	390	0.94%	8.69%	324	0.19%	10.41%	528	0.11%	5.42%	528	0.22%	9.44%	346	0.68%	7.16%	220	-0.53%	7.48%	220	-1.00%	6.68%	308	0.17%	6.92%
5	390	0.94%	8.35%	324	0.11%	9.22%	528	0.10%	5.30%	528	0.24%	9.42%	346	0.72%	7.08%	220	-0.46%	7.45%	220	-0.95%	6.62%	308	0.18%	6.89%
6	390	0.93%	8.07%	324	0.09%	8.57%	528	0.11%	5.27%	528	0.23%	9.42%	346	0.74%	6.98%	220	-0.41%	7.37%	220	-0.86%	6.56%	308	0.21%	6.79%
7	390	0.92%	7.81%	324	0.11%	7.93%	528	0.11%	5.30%	528	0.24%	9.41%	346	0.74%	6.90%	220	-0.39%	7.17%	220	-0.81%	6.41%	308	0.17%	6.56%
8	390	0.89%	7.60%	324	0.20%	7.55%	528	0.11%	5.44%	528	0.25%	9.40%	346	0.74%	6.82%	220	-0.40%	6.88%	220	-0.77%	6.27%	308	0.18%	6.40%
9	390	0.87%	7.42%	324	0.26%	7.12%	528	0.11%	5.45%	528	0.27%	9.38%	346	0.74%	6.73%	220	-0.42%	6.70%	220	-0.73%	6.10%	308	0.21%	6.22%
10	390	0.84%	7.25%	324	0.38%	6.90%	528	0.10%	5.45%	528	0.28%	9.35%	346	0.74%	6.66%	220	-0.44%	6.48%	220	-0.68%	5.93%	308	0.21%	6.07%
11	390	0.81%	7.10%	324	0.43%	6.66%	528	0.09%	5.45%	528	0.32%	9.18%	346	0.74%	6.60%	n/a	n/a	n/a	n/a	n/a	n/a	308	0.19%	5.84%
12	390	0.80%	6.97%	324	0.40%	6.41%	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a	n/a

Note: This table provides an overview of the futures data set. The data set consists of eight commodities (oil, gas, gold, silver, copper, wheat, corn, soybean) from three groups (energy, metals, grains). Rows three and four give the start dates and end dates of the data periods for the different commodities. The following rows deliver information on futures contracts. They show the times to maturities ($T - t$) in months, the number of available observations (obs.) over the respective data periods, and the means (μ) and standard deviations (σ) of monthly futures returns.

Table 3.1 gives an overview of the data set and the monthly (simple) futures returns. It summarizes the data periods and numbers of observations for all commodities. Moreover, for each commodity and each maturity, it provides the mean futures return and the return standard deviation. Depending on the commodity, mean returns can be entirely negative (corn) or entirely positive (oil) over the whole range of maturities, or change their sign (gas). In terms of economic significance—with the interpretation of futures returns as returns of fully collateralized investments—the magnitude of mean returns can be very substantial. For example, the 0.99% mean return of the one-month copper futures leads to an annualized value of about 12%, earned over a period of about 30 years. There are also some substantially negative mean returns, like the -1% monthly return of the three-months corn futures. Mean returns can also differ substantially between futures written on the same commodity, depending on the time to maturity. For example, one-month wheat futures have an average monthly return of 0.19%, compared to an average monthly return of -0.44% of ten-months wheat futures. Therefore, we see at least some variation in average realized term premiums. Another important observations is that futures returns show high standard deviations. For example, the monthly return standard deviation of the one-month copper futures is 7.55%, leading to a monthly Sharpe ratio of about 0.13 and an annualized one of about 0.45.

Substantial mean returns and return differences between contracts with different maturities suggest the existence of some structure in term premiums and some potential to earn them. However, high standard deviations make this a challenging task. The idea pursued in this paper is to use the model-based factor decomposition of expected futures returns, as introduced in Section 3.2, to generate signals that are potentially useful in trading strategies. Before we do so in Section 3.5, however, we take a closer look at the questions of how well the suggested factor model is able to capture the empirical structure of futures returns and how many factors are necessary.

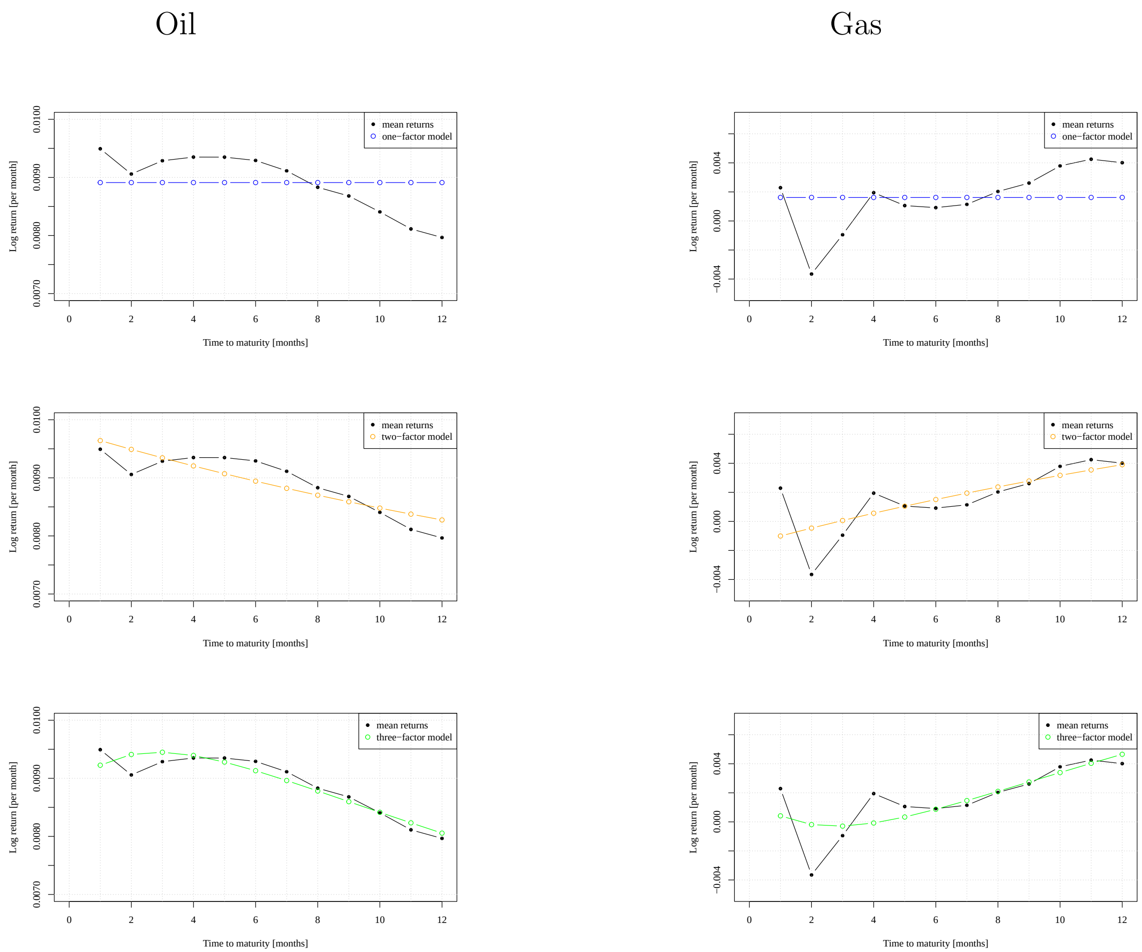
3.4 How Many Factors?

Equation (3.3) together with the specification of the g functions from Figure 3.1 delivers a simple visualization of how the factor model describes the term structure of expected futures returns. According to Equation (3.3), the log expected futures returns for different maturities are just combinations of a constant, a linear term and a non-linear term. This simple framework also helps to identify how many factors are needed to describe term premiums of different commodities. If the term structure of expected futures returns is flat, a one-factor model is sufficient.[6] If the term structure is upward or downward sloping but has an (almost) linear form, the two-factor model leads to an adequate characterization. If the term structure shows a strongly non-linear shape, a third factor is required. Moreover, if this non-linear shape is not generally concave or convex over the whole range of maturities, even a three-factor model may be too restrictive.

Figures 3.2 to 3.4 provide plots of the log mean returns of commodity futures against the respective times to maturity for energy, metals and grains. For each commodity, the figure includes three graphs. Each graph adds the model-based expected return curve arising from a one-factor, a two-factor and a three-factor model, respectively, obtained via OLS regressions. Figures 3.2 to 3.4 deliver several interesting observations. (i) There is not a single commodity where a one-factor model provides an adequate fit to the log expected futures returns. (ii) There is also no commodity where the log mean returns suggest a linear structure. This observation could mean two things. First, a two-factor model specification should use a "level factor" plus a "curvature factor" instead of a "slope factor". Second, two factors are not enough to explain the term structure. This second interpretation seems to be at odds with the popularity of two-factor pricing models, e.g., the long-term-short-term model, in practice. However, the same model may perform well or not so well, depending on the question under study. One dimension is pricing, i.e., the term structure of futures prices. A second important aspect is the term structure of volatilities which is required for option pricing. The topic of this paper is yet another context: the term structure of expected futures returns. Therefore, a more parsimonious model may be sufficient for one dimension while a richer model may be required for another context. (iii) Some form of non-linearity of the term structure of expected futures returns is important for all commodities. (iv) Even the three-factor specification is not sufficient to explain the term structure of expected futures returns for all commodities, as the log mean return curve for gas has both convex and concave parts.

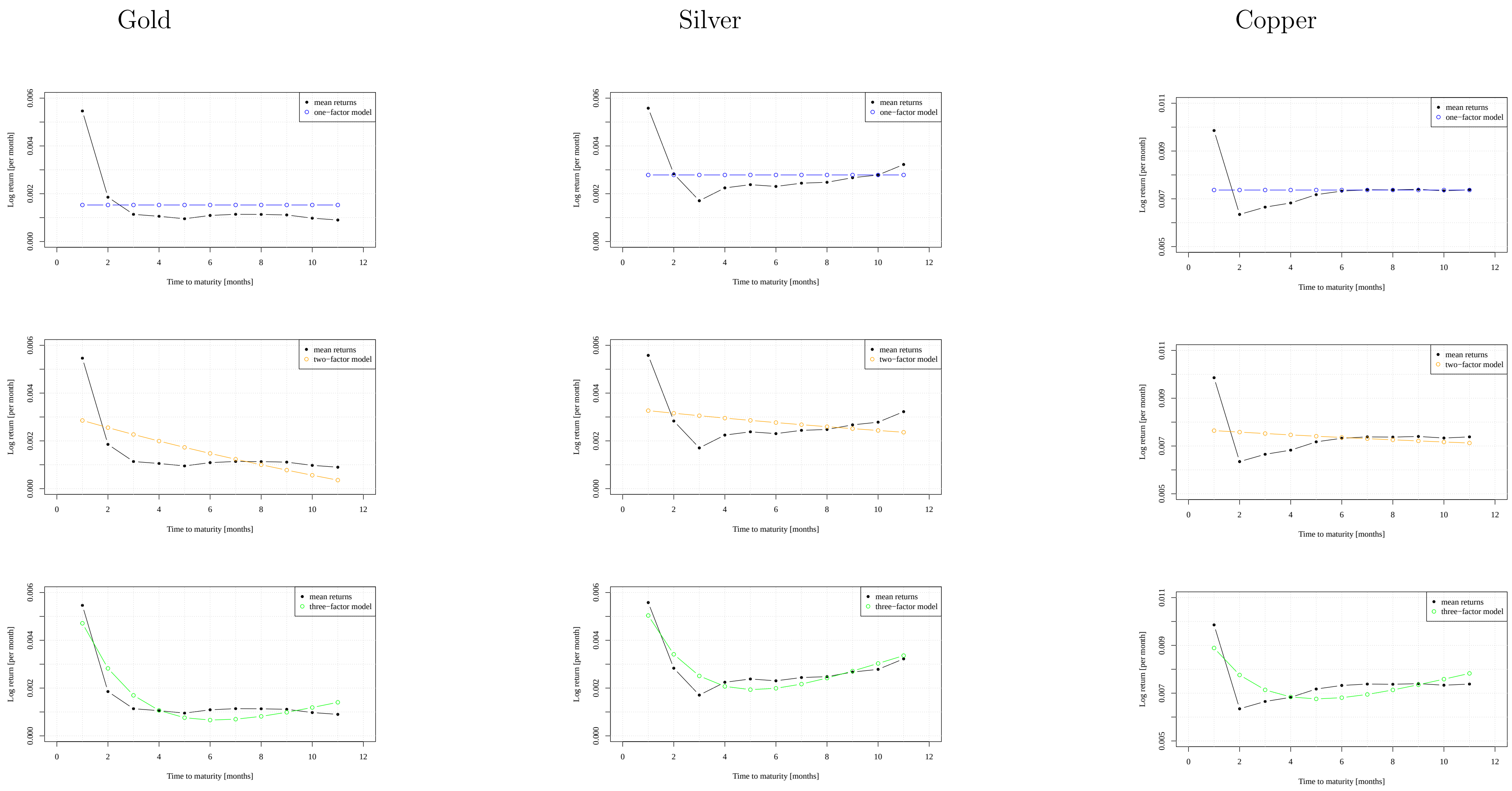
[6]The special case of a term structure that is flat at zero means that no premiums are to be explained. In this sense, a "zero-factor model" would be sufficient.

Figure 3.2: Mean Futures Returns and Fitted Expected Return Curves: Energy



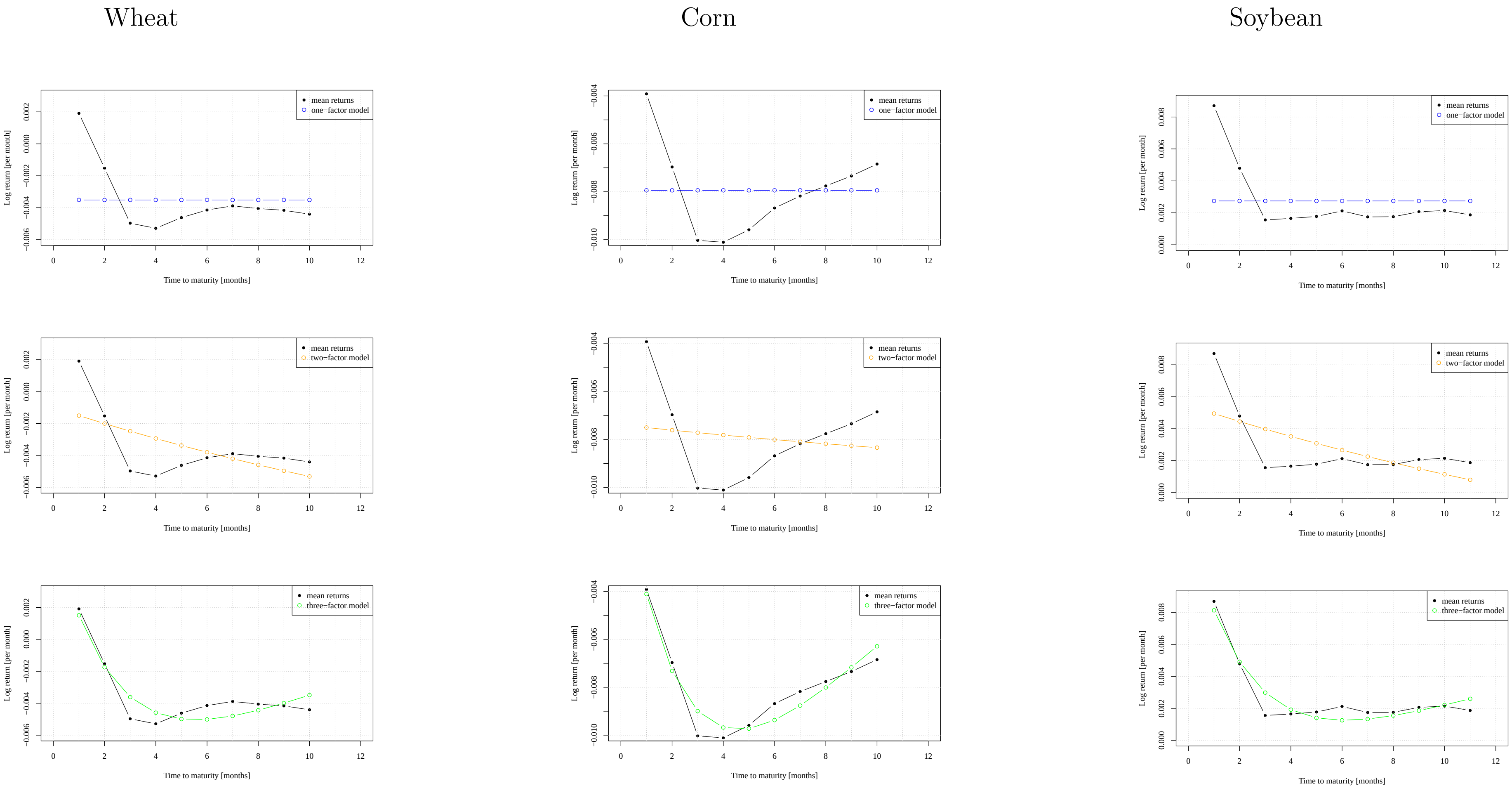
Note: This figure shows the logs of the mean monthly returns of futures contracts for oil and gas, together with fitted model-based expected return curves. Monthly mean returns are calculated for maturities between one and twelve months for the entire sample period, which is given in Table 3.1. Fitted expected return curves refer to three different model variants. The first variant is a one-factor model, leading to a flat curve; the second is a two-factor model, allowing for a linear curve with non-zero slope; and the third is a three-factor model, allowing for a non-linear curve.

Figure 3.3: Mean Futures Returns and Fitted Expected Return Curves: Metals



Note: This figure shows the logs of the mean monthly returns of futures contracts for gold, silver and copper, together with fitted model-based expected return curves. Monthly mean returns are calculated for maturities between one and eleven months for the entire sample period, which is given in Table 3.1. Fitted expected return curves refer to three different model variants. The first variant is a one-factor model, leading to a flat curve; the second is a two-factor model, allowing for a linear curve with non-zero slope; and the third is a three-factor model, allowing for a non-linear curve.

Figure 3.4: Mean Futures Returns and Fitted Expected Return Curves: Grains



Note: This figure shows the logs of the mean monthly returns of futures contracts for wheat, corn and soybean, together with fitted model-based expected return curves. Monthly mean returns are calculated for maturities between one and ten (wheat, corn) or eleven (soybean) months for the entire sample period, which is given in Table 3.1. Fitted expected return curves refer to three different model variants. The first variant is a one-factor model, leading to a flat curve; the second is a two-factor model, allowing for a linear curve with non-zero slope; and the third is a three-factor model, allowing for a non-linear curve.

To substantiate the visual impression from Figures 3.2 to 3.4, regression results for the three-factor model are reported in Table 3.2. The table shows the estimates of the factor loadings (lambdas) together with the corresponding t-statistics (in parantheses) for each commodity. As measures of fit, the centered as well as the uncentered coefficient of determination (R^2) are provided, since both measures correspond to sensible reference points. One such reference point is a flat term structure at zero, because any non-zero term premiums require some priced risk, even if the term structure is flat. The uncentered R^2 delivers the corresponding improvement in fit due to the three-factor model. The centered R^2, in contrast, measures whether the three-factor model can improve the fit compared to the one-factor model. For all commodities, except for gas, all three lambda parameters are statistically significant. This result suggests that all three factors are usually required to describe expected return curves adequately. Moreover, the uncentered R^2s for all commodities, again with the exception of gas, are above 0.9, confirming the visual impression that the three-factor model delivers a good fit of the average term premiums. The comparison between centered and uncentered R^2s shows that the second and third factor improve the fit massively. The only exception is copper, where the centered R^2 is below 0.5.

Table 3.2: Estimated Factor Loadings of the Three-Factor Model

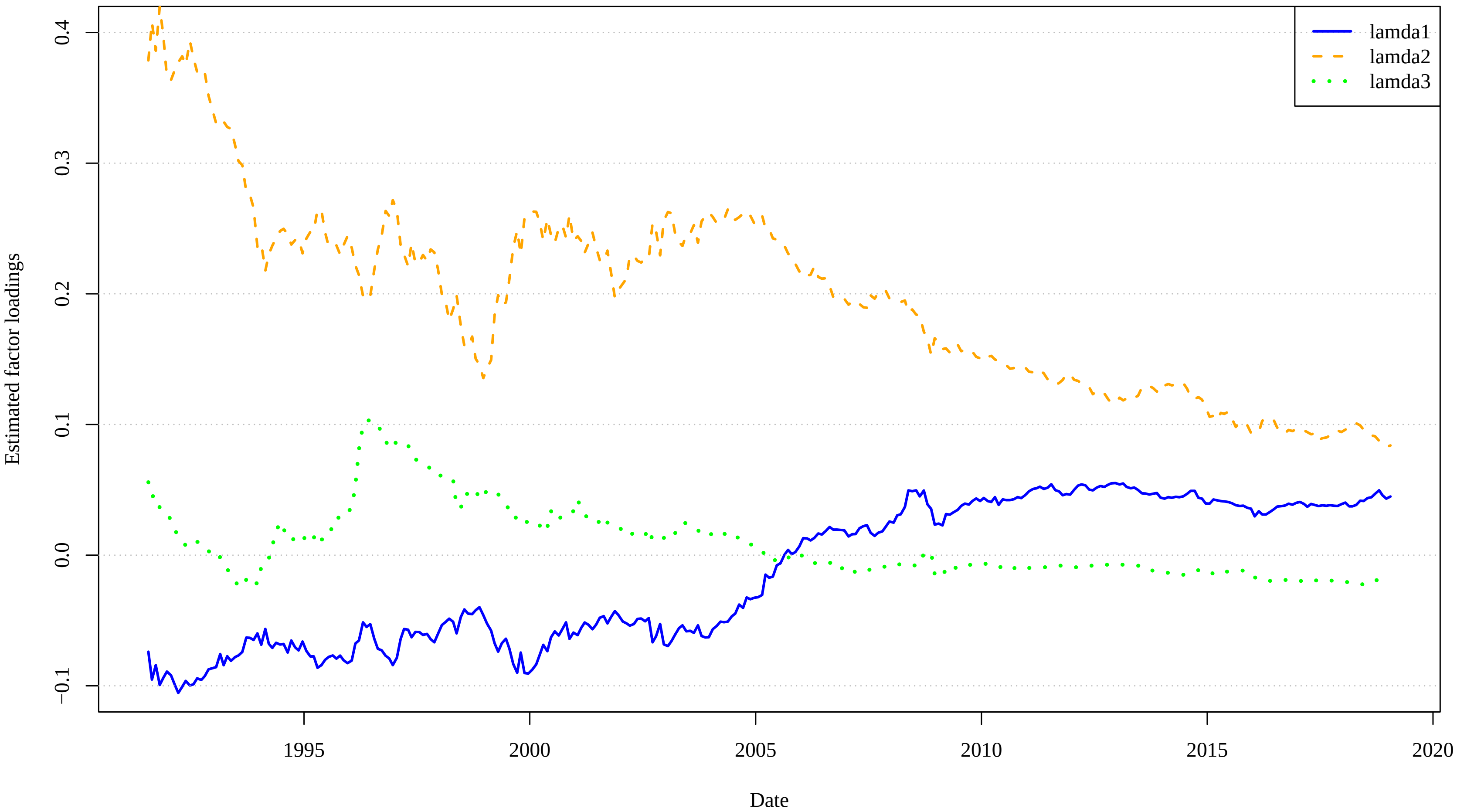
	Energy		**Metals**			**Grains**		
Coefficient	Oil	Gas	Gold	Silver	Copper	Wheat	Corn	Soybean
λ_1	0.0448	0.2378	0.0919	0.1461	0.1712	0.1365	0.2164	0.1638
	(5.047)	(3.221)	(2.754)	(5.365)	(4.112)	(2.194)	(4.893)	(3.932)
λ_2	0.0839	-0.2947	-0.1181	-0.1656	-0.1209	-0.2701	-0.4393	-0.2087
	(6.686)	(-2.825)	(-2.553)	(-4.387)	(-2.094)	(-3.191)	(-7.300)	(-3.612)
λ_3	-0.0200	0.0683	0.0983	0.0937	0.0660	0.1787	0.2013	0.1691
	(-3.431)	(1.409)	(4.968)	(5.803)	(2.672)	(5.399)	(8.551)	(6.848)
maturities	12	12	11	11	11	10	10	11
centered R^2	0.8941	0.7161	0.8502	0.8252	0.4909	0.8746	0.9146	0.9126
uncentered R^2	0.9997	0.7520	0.9390	0.9815	0.9932	0.9682	0.9960	0.9683

Note: This table shows the estimated factor loadings (lambdas) of the three-factor model for all eight commodities. The estimates are obtained via OLS-regressions of the log mean futures returns for different maturities on the three g-functions with $\kappa = 0$, $\kappa = 0.5$, and $\kappa = 5$, as shown in Figure 3.1. t-values are given in parentheses. In addition, the number of different maturities and the uncentered R^2 are reported.

So far, we used mean returns, calculated over the entire sample period. An important issue, which we will carry on with in the next section, is whether the model-based factor characterization of expected returns, as shown in Table 3.2, is sufficiently stable over time. To provide a first impression on this issue, we use the first five years of the respective data periods of the different commodities to obtain initial estimates of the lambda parameters in the three-factor model. The estimates are obtained from a non-linear least squares pooled panel regression, based on Equation (3.1). Starting with these estimates, we extend the estimation window month by month, receiving new parameter estimates on a monthly basis. At the end of the data period, these estimates converge to the values in Table 3.2.

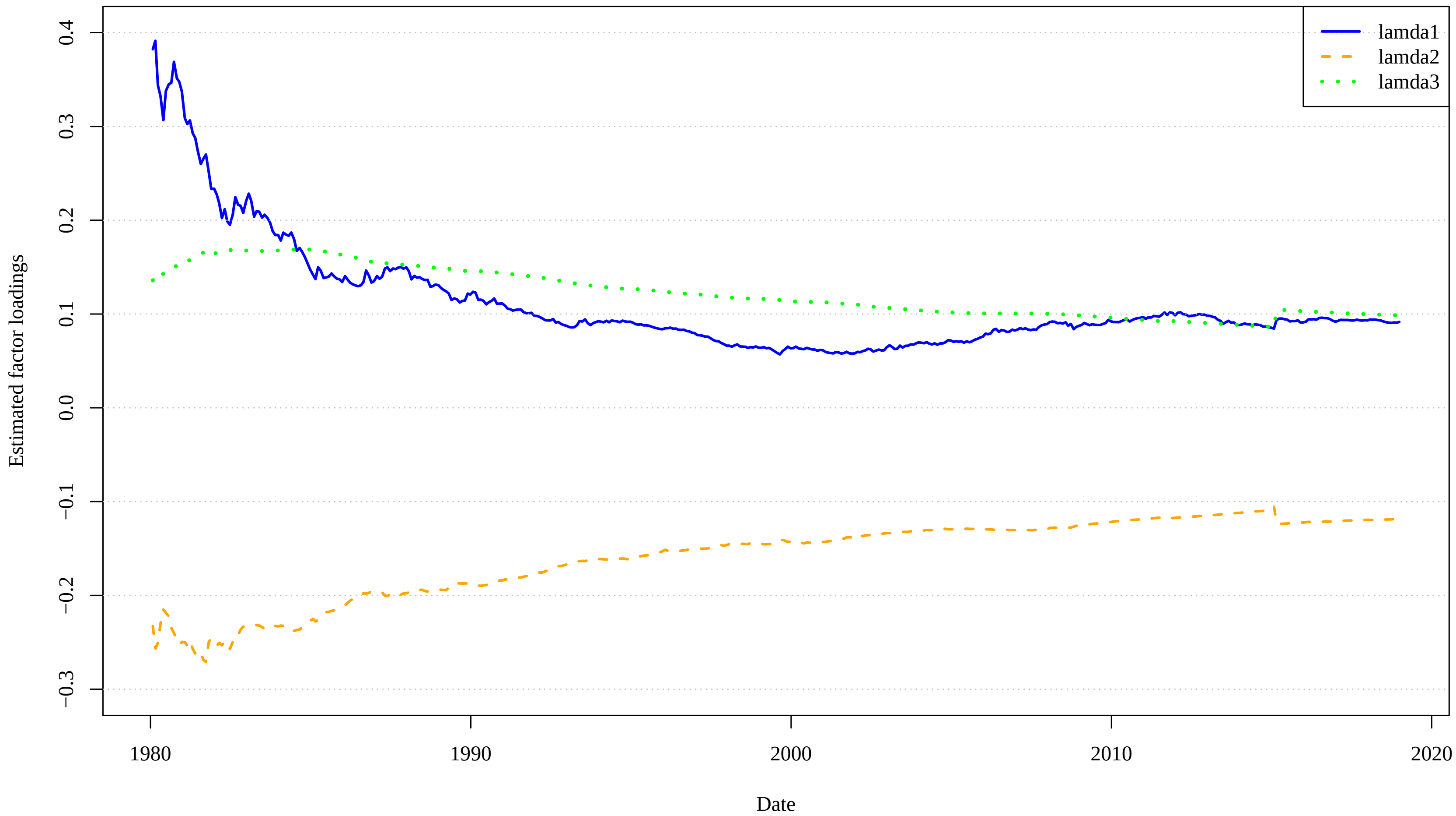
Figures 3.5 to 3.7 show the evolution of lambda estimates for one commodity from each group: crude oil, gold, and wheat. Parameter estimates for oil are not very stable in the sense that both λ_1 and λ_3 change their sign over time. In particular, during the period from about 2004 to 2008, lambda estimates suggest substantial changes in the term structure of expected futures returns. Such a finding is well in line with other changes in oil futures markets. Kang, Nikitopoulos, and Prokopczuk (2020) find significant changes in drivers of short-term and medium-term volatilities after 2004, which are plausibly linked to the financialization of commodity markets. Moreover, the 2004 to 2008 period saw massive increases in oil prices. Therefore, estimates of expected returns are likely to increase when this period enters the estimation window. For gold and wheat, there is also some variation over time. In particular, wheat shows significant changes in lambda estimates during the food price crisis from August 2007 to February 2008. However, the signs of all three parameters stay the same over the entire period for wheat and gold, leading to generally convex expected return curves.

Figure 3.5: Estimated Factor Loadings for Oil: Expanding Window



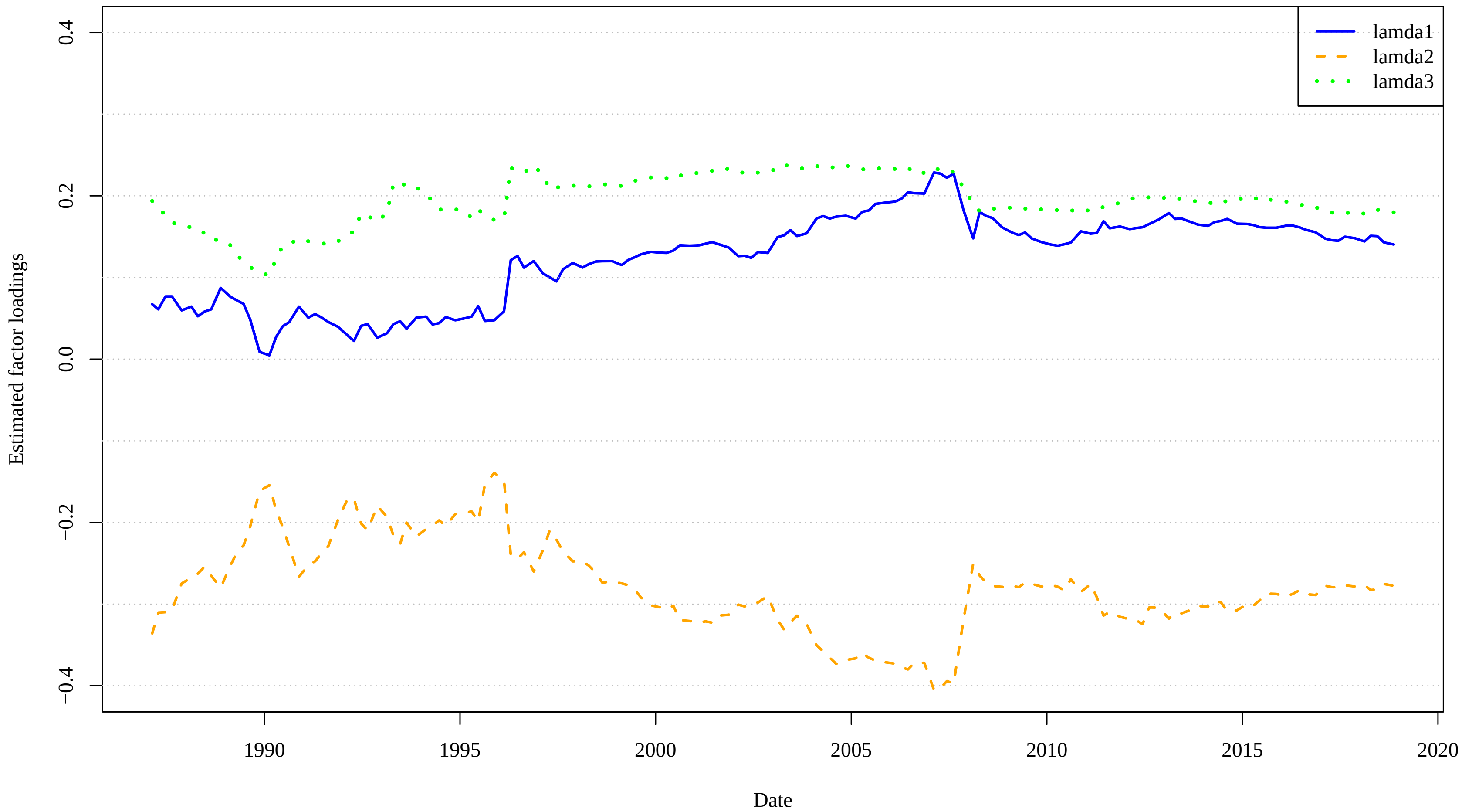
Note: This figure shows the development of the estimated factor loadings (lambdas) of the three-factor model for oil over time. Estimates use an expanding data window. The initial estimates are obtained from the futures prices of all maturities up to twelve months for the first five years of the data period.

Figure 3.6: Estimated Factor Loadings for Gold: Expanding Window



Note: This figure shows the development of the estimated factor loadings (lambdas) of the three-factor model for gold over time. Estimates use an expanding data window. The initial estimates are obtained from the futures prices of all maturities up to eleven months for the first five years of the data period.

Figure 3.7: Estimated Factor Loadings for Wheat: Expanding Window



Note: This figure shows the development of the estimated factor loadings (lambdas) of the three-factor model for wheat over time. Estimates use an expanding data window. The initial estimates are obtained from the futures prices of all maturities up to ten months for the first five years of the data period.

3.5 Factor-based Trading Strategies

This section examines whether the proposed three-factor model delivers informative signals on term premiums in commodity futures markets. The metric that we use to answer this questions are the returns of a number of designed trading strategies. In total we consider three types of trading strategies: the first one, which we call a "level strategy", buys one futures contract if the model signals a positive premium, i.e., a positive expected return of that contract. If the expected return is negative, one contract is sold. In principle, a level strategy can be implemented for any contract with any time to maturity. Because short-term futures contracts are usually much more liquid than long-term futures, we use the shortest-maturity contracts in our data set—the one-month futures—to implement the level strategy. To obtain the signal, we use Equation (3.4) to calculate the expected return of a one-month future that is held until maturity ($T-t$ and h both equal one month). The functions g use $\kappa_1 = 0, \kappa_2 = 0.5$, and $\kappa_3 = 5$. Lambdas are estimates from the panel regressions, as shown in Figures 3.5 to 3.7. For example, with $\lambda_1 = 0.05, \lambda_2 = 0.08$, and $\lambda_3 = -0.02$, which are realistic values for oil, we obtain a positive expected return of about 11.25% p.a., i.e., the signal suggests to buy the one-month futures. A second strategy is the "slope strategy". It buys one long-term contract and sells one short-term contract if the model signals a positive return difference, i.e., an upward sloping term structure of expected futures returns. If there is a signal of a downward sloping term structure, a long-term contract is sold and a short-term contract is bought. To implement the slope strategy, we use the longest-maturity contract (either ten, eleven or twelve months) as well as the contract with the shortest maturity (one month) and calculate their expected returns according to Equation (3.4). The third strategy is called the "curvature strategy" and tries to exploit nonlinearities in the term structure of expected futures returns. This strategy buys one long-term and one short-term contract and sells two medium-term contracts if the model signals a positive portfolio return, i.e, a convex term structure. If the model signals concavity, long- and short-term futures are sold and medium-term futures are bought. The medium-term contract's time to maturity is six months if the long-term contracts are either eleven- or twelve-months contracts and is five months otherwise. All trading strategies use a monthly holding period.

Model-based signals are generated in three different ways. All three variants use the three-factor model and the same g functions ($\kappa_1 = 0, \kappa_2 = 0.5, \kappa_3 = 5$) to determine expected returns, but differ in how lambdas are estimated. The first variant (full sample) uses the whole panel data set for the estimation. Of course, trading strategies based on the signals from this variant use in-sample information and cannot be implemented ex ante. However, they provide interesting reference points that help our understanding of how the results on model adequacy from Section 3.4 translate into returns. Also note that "full sample" signals are the same for all months in the data period, therefore achieving the maximum amount of "stability" of a trading strategy. The second variant (expanding window) uses the first five years of the data period to obtain initial lambda estimates, which are then used to obtain signals for the first monthly investment period. After a month, the estimation window is expanded by one month and the updated estimates are used to calculate signals for the next month. This procedure is continued until the end of the data period.[7] The "expanding window" signals are available ex ante. Since lambda estimates use more and more data information over time, signals will usually also become more stable over time. The third variant (rolling window) uses a five-years rolling window to estimate the lambdas. With a rolling estimation window, the model is able to adapt to time variation in the term structure of expected futures returns. However, a disadvantage, as compared to the expanding window variant, is the lower number of observations in each time step that could lead to larger estimation errors and unstable signals.

In the following, for all variants, monthly returns of the level-, slope- and curvature strategies are calculated for all commodities. The first five years of the data period, which are needed to obtain initial estimates under the expanding window and the rolling window variants, are not used for evaluation even in the full sample variant to achieve a clean comparison between the three variants.

[7] The lambda estimates of the "expanding window" variant are the ones shown in Figure 3.5 to 3.7.

Table 3.3: Returns of Trading Strategies – Full Sample Signal

Level Strategy

	Energy		Metals			Grains		
	Oil	Gas	Gold	Silver	Copper	Wheat	Corn	Soybean
Contracts	1	1	1	1	1	1	1	1
Mean	7.46%	8.22%	3.81%	1.29%	11.05%	7.02%	3.85%	8.19%
Std. Dev.	34.35%	54.27%	17.65%	31.64%	26.95%	29.90%	23.72%	23.50%
T-Stat.	1.1390	0.7100	1.3488	0.2542	2.0008	0.8571	0.5923	1.5689
P-Value	0.2555	0.4783	0.1780	0.7994	0.0464	0.3927	0.5545	0.1180
Sharpe Ratio	21.72%	15.14%	21.60%	4.07%	40.98%	23.47%	16.22%	34.86%
Hit Ratio	53.64%	56.44%	49.15%	45.09%	52.80%	46.88%	51.25%	54.73%
Observations	330	264	468	468	286	160	160	243

Slope Strategy

	Energy		Metals			Grains		
	Oil	Gas	Gold	Silver	Copper	Wheat	Corn	Soybean
Contracts	1,12	1,12	1,11	1,11	1,11	1,10	1,10	1,11
Mean	0.81%	12.12%	5.47%	2.09%	2.48%	8.28%	1.98%	7.15%
Std. Dev.	18.21%	38.15%	5.85%	7.00%	7.33%	14.85%	11.26%	12.59%
T-Stat.	0.2335	1.4904	5.8369	1.8629	1.6536	2.0364	0.6405	2.5575
P-Value	0.8155	0.1373	0.0000	0.0631	0.0993	0.0434	0.5228	0.0112
Sharpe Ratio	4.45%	31.78%	93.47%	29.83%	33.87%	55.77%	17.54%	56.83%
Hit Ratio	53.33%	57.95%	85.68%	69.02%	54.20%	54.38%	52.50%	54.32%
Observations	330	264	468	468	286	160	160	243

Curvature Strategy

	Energy		Metals			Grains		
	Oil	Gas	Gold	Silver	Copper	Wheat	Corn	Soybean
Contracts	1,6,12	1,6,12	1,6,11	1,6,11	1,6,11	1,5,10	1,5,10	1,6,11
Mean	2.35%	1.49%	4.89%	5.01%	3.57%	7.50%	9.14%	8.73%
Std. Dev.	10.88%	30.79%	5.66%	9.43%	5.22%	12.82%	10.88%	11.42%
T-Stat.	1.1306	0.2274	5.3928	3.3153	3.3353	2.1371	3.0668	3.4377
P-Value	0.2590	0.8203	0.0000	0.0010	0.0010	0.0341	0.0025	0.0007
Sharpe Ratio	21.56%	4.85%	86.35%	53.09%	68.32%	58.53%	83.99%	76.39%
Hit Ratio	56.97%	52.65%	93.16%	86.75%	68.18%	60.63%	66.25%	64.20%
Observations	330	264	468	468	286	160	160	243

Note: This table reports the results of trading strategies with futures contracts based on signals from the full sample. It covers level strategies, slope strategies and curvature strategies. Returns are reported as annualized values. The trading signals are obtained via the three-factor model, based on parameter estimates from the full sample. The reported results leave out the first five years of the respective data periods to make the results comparable to the ones obtained from an out-of-sample approach using an expanding or rolling window.

Table 3.3 reports the results of the trading strategies based on full sample signals. As pointed out before this strategy cannot be implemented in a real world setting, since the models are estimated using the entire sample period. Mean returns, return standard deviations and Sharpe ratios are reported as annualized values. In addition, the table provides the t-statistics and p-values for the mean returns as well as the percentage of months where the model predicts the sign of the realized return correctly (hit ratio). Because full sample signals do not change over time, level strategies just hold a long futures contract for oil, gas, gold, silver, copper, wheat and soybean. For corn, the level strategy takes a short position in the one-month futures. Level strategies based on the full sample signals are able to earn substantial mean returns of up to 11 percent per year (copper). However, they are also very risky, leading to substantial standard deviations. Copper is the only commodity with statistically significant mean returns, being only marginally significant at the five-percent level. Full sample signals for the slope strategy indicate a downward sloping term structure for all commodities except for gas. Mean returns for the slope strategies can also be very substantial and even higher than for the level strategies (for gas, gold, silver, wheat). However, for all commodities the return standard deviation is much lower for the slope strategy in comparison to the level strategy. Because slope strategies are long-short strategies, they hedge out changes in the overall futures price level and are left with the remaining risk of distortions between futures of different maturities. Slope strategies obtain statistically significant mean returns for gold, wheat and soybean, reaching annual Sharpe ratios above 0.5 for these commodities. Full sample signals for curvature strategies indicate convexity of the term structure of expected futures returns for all commodities except for oil. Like for the slope strategy, curvature strategies implement a long-short trading strategy. In principle, the way the strategy is constructed will provide a hedge against changes of the commodity price level and against changes in the slope of the futures curve. Actually, for seven out of eight commodities, the standard deviation of generated return by the curvature strategy is lower than for the slope strategy. Mean returns of curvature strategies, though, can still be high. These mean returns are statistically significant at the one-percent level for all metals and all grains. Overall, the potential to earn significant returns seems to increase from level- to slope- and curvature strategies. This is an interesting finding, because it indicates that there is some structure in term premiums of futures contracts and that the signals from the applied factor models are potentially useful for extracting this information. However, we have to further investigate whether the trading strategies are also useful in an actual ex ante setting.

Table 3.4 shows the results for trading strategies set up according to the expanding window signals. For level strategies, we see very little difference to the full sample variant. Actually, for metals and grains, the results are exactly identical because the signals of the expanding window variant are exactly identical to the ones of the full sample variant. This result comes with little surprise for gold and wheat, since Figures 3.6 and 3.7 illustrate that the expanding window estimates for lambdas did not exhibit any change in sign over the sample period. For gas, some serious changes in signals occurred, but these changes did not improve the results for the level strategy. To the contrary, mean returns became even negative. Similar observation are made for slope and curvature strategies. The expanding window signals for metals and grains are very stable. For oil and gas, signals are less stable but still do not lead to any significant mean returns. Overall, we can conclude that commodities yielding significant returns from slope and curvature strategies under the full sample variant continue to do so if ex-ante signals from an expanding window are used. The reason is the stability of signals over the whole data period. For oil and gas, however, where some changes in signals are observed, the performance of trading strategies diminishes, suggesting that the signals are more likely to capture mere noise rather than time variation of the term premiums.

In the final step of our analysis, we examine whether the performance of the strategies can be improved by potentially allowing for more time variation in signals, based on a rolling estimation window. Stated differently, we investigate whether five years of data is enough for the three-factor model to pick up a sufficient amount of structure in term premiums from rather volatile futures returns. Table 3.5 shows annualized means and standard deviations for the three types of trading strategies under the rolling window variant. Obtained results suggest that the rolling window approach does not improve the performance of the trading strategies. For the level strategies, there is no significant mean return for any commodity. For the slope strategies, both wheat and soybean lose their significant mean returns. The rather low number of observations for these commodities makes it apparently difficult to obtain informative signals from only five years of data. Similar observations are made for the curvature strategy. The factor model does not seem to generate reliable signals on the curvature of the expected return curve because only gold, copper and wheat continue to show significant mean returns. For silver, corn and soybean the hit ratios drop substantially, as compared to expanding window signals. Gold is

Table 3.4: Returns of Trading Strategies – Expanding Window Signal

Level Strategy

	Energy		Metals			Grains		
	Oil	Gas	Gold	Silver	Copper	Wheat	Corn	Soybean
Contracts	1	1	1	1	1	1	1	1
Mean	7.77%	-13.36%	3.81%	1.29%	11.05%	-1.52%	3.85%	8.19%
Std. Dev.	34.37%	54.18%	17.65%	31.64%	26.95%	29.97%	23.72%	23.50%
T-Stat.	1.1841	-1.1565	1.3488	0.2542	2.0008	-0.1856	0.5923	1.5689
P-Value	0.2372	0.2485	0.1780	0.7994	0.0464	0.8530	0.5545	0.1180
Sharpe Ratio	22.61%	-24.66%	21.60%	4.07%	40.98%	-5.08%	16.22%	34.86%
Hit Ratio	53.80%	41.67%	49.15%	45.09%	52.80%	41.25%	51.25%	54.73%
Observations	330	264	468	468	286	160	160	243

Slope Strategy

	Energy		Metals			Grains		
	Oil	Gas	Gold	Silver	Copper	Wheat	Corn	Soybean
Contracts	1,12	1,12	1,11	1,11	1,11	1,10	1,10	1,11
Mean	-0.67%	-3.59%	5.47%	2.09%	2.48%	8.28%	1.98%	7.15%
Std. Dev.	18.22%	38.30%	5.85%	7.00%	7.33%	14.85%	11.26%	12.59%
T-Stat.	-0.1913	-0.4401	5.8369	1.8629	1.6536	2.0364	0.6405	2.5575
P-Value	0.8484	0.6602	0.0000	0.0631	0.0993	0.0434	0.5228	0.0112
Sharpe Ratio	-3.65%	-9.38%	93.47%	29.83%	33.87%	55.77%	17.54%	56.83%
Hit Ratio	46.81%	49.62%	85.68%	69.02%	54.20%	54.38%	52.50%	54.32%
Observations	330	264	468	468	286	160	160	243

Curvature Strategy

	Energy		Metals			Grains		
	Oil	Gas	Gold	Silver	Copper	Wheat	Corn	Soybean
Contracts	1,6,12	1,6,12	1,6,11	1,6,11	1,6,11	1,5,10	1,5,10	1,6,11
Mean	-2.29%	-6.69%	4.89%	5.01%	3.19%	7.50%	6.88%	8.73%
Std. Dev.	10.90%	30.73%	5.66%	9.43%	5.24%	12.82%	11.02%	11.42%
T-Stat.	-1.1000	-1.0210	5.3928	3.3153	2.9687	2.1371	2.2802	3.4377
P-Value	0.2722	0.3082	0.0000	0.0010	0.0032	0.0341	0.0239	0.0069
Sharpe Ratio	-21.01%	-21.77%	86.35%	53.09%	60.81%	58.53%	62.45%	76.39%
Hit Ratio	43.16%	45.45%	93.16%	86.75%	67.48%	60.63%	58.13%	64.20%
Observations	330	264	468	468	286	160	160	243

Note: This table reports the results of trading strategies with futures contracts based on signals from an expanding window. It covers level strategies, slope strategies and curvature strategies. Returns are reported as annualized values. The trading signals are obtained via the three-factor model, based on parameter estimates from an expanding window. Initial estimates are obtained from the first five years of the respective data periods.

Table 3.5: Returns of Trading Strategies – Rolling Window Signal

Level Strategy

	Energy		Metals			Grains		
	Oil	Gas	Gold	Silver	Copper	Wheat	Corn	Soybean
Contracts	1	1	1	1	1	1	1	1
Mean	9.94%	10.01%	3.43%	1.46%	5.68%	-11.47%	-3.78%	3.98%
Std. Dev.	34.30%	54.24%	17.66%	31.64%	27.09%	29.79%	23.72%	23.59%
T-Stat.	1.5200	0.8657	1.2121	0.2882	1.0227	-1.4065	-0.5815	0.7601
P-Value	0.1295	0.3874	0.2261	0.7733	0.3073	0.1615	0.5617	0.4479
Sharpe Ratio	28.98%	18.46%	19.41%	4.61%	20.95%	-38.52%	-15.93%	16.89%
Hit Ratio	52.42%	49.24%	52.56%	50.21%	50.70%	43.13%	47.50%	51.03%
Observations	330	264	468	468	286	160	160	243

Slope Strategy

	Energy		Metals			Grains		
	Oil	Gas	Gold	Silver	Copper	Wheat	Corn	Soybean
Contracts	1,12	1,12	1,11	1,11	1,11	1,10	1,10	1,11
Mean	4.24%	-2.90%	5.47%	1.91%	-0.04%	5.89%	1.40%	5.08%
Std. Dev.	18.17%	38.30%	5.85%	7.00%	7.36%	14.94%	11.27%	12.67%
T-Stat.	1.2236	-0.3557	5.8369	1.7071	-0.0250	1.4383	0.4547	1.8046
P-Value	0.2220	0.7223	0.0000	0.0885	0.9801	0.1523	0.6500	0.0724
Sharpe Ratio	23.33%	-7.58%	93.47%	27.34%	-0.51%	39.39%	12.45%	40.10%
Hit Ratio	46.67%	49.62%	85.68%	69.02%	54.20%	54.38%	52.50%	54.32%
Observations	330	264	468	468	286	160	160	243

Curvature Strategy

	Energy		Metals			Grains		
	Oil	Gas	Gold	Silver	Copper	Wheat	Corn	Soybean
Contracts	1,6,12	1,6,12	1,6,11	1,6,11	1,6,11	1,5,10	1,5,10	1,6,11
Mean	1.60%	-10.47%	4.03%	1.45%	2.77%	7.50%	0.56%	2.45%
Std. Dev.	10.89%	30.64%	5.72%	9.53%	5.26%	12.82%	11.20%	11.68%
T-Stat.	0.7702	-1.6024	4.4014	0.9523	2.5707	2.1371	0.1819	0.9436
P-Value	0.4417	0.1103	0.0000	0.3415	0.0106	0.0341	0.8559	0.3463
Sharpe Ratio	14.69%	-34.16%	70.48%	15.25%	52.66%	58.53%	4.98%	20.97%
Hit Ratio	49.70%	46.21%	89.96%	55.13%	67.13%	60.63%	45.00%	52.26%
Observations	330	264	468	468	286	160	160	243

Note: This table reports the results of trading strategies with futures contracts based on signals from a rolling window. It covers level strategies, slope strategies and curvature strategies. Returns are reported as annualized values. The trading signals are obtained from the three-factor model, based on parameter estimates from a five-year rolling window. Initial estimates are obtained from the first five years of the respective data periods.

the only commodity with significant mean returns for both slope and curvature strategies. The reason is that for gold the signals are extremely stable even when a rolling window estimation approach is applied. Typically, for gold, the signals for the rolling window based strategy remain the same as for the full sample variant.

In summary, our results indicate that the applied three-factor model does provide ex ante information on the slope and in particular the curvature of the term structure of expected futures returns for metals and grains. To extract this information, the estimation period needs to be long enough, i.e., sufficient data information in the time dimension is required. For oil and gas, any term premiums—if they do exist—can not be extracted via the three-factor model, presumably due to a low signal to noise ratio in futures returns.

3.6 Conclusions

This paper documents some persistent patterns in the term structure of expected commodity futures returns. Expected returns are derived under the N-factor valuation model by Cortazar and Naranjo (2006); and the subset of remaining model parameters is estimated from futures prices. This approach has the advantage that it offers great flexibility in modeling the expected return curves, while taking into account the close relationship between futures contracts of different maturities via an arbitrage-free pricing model. As our empirical results for eight commodities show, such flexibility is needed because expected return curves can differ substantially between commodities. Another advantage is that latent factors can in principle pick up effects that result from multiple economic sources. Examples for such sources are hedging and liquidity demand,[8] differences in liquidity between futures with different times to maturity or the risk of physical delivery that holders of short-term futures contracts face after the notice day.

The corresponding disadvantage of our approach is, of course, that the specific sources of term premiums stay hidden. Connecting our approach to a more fundamental view on term premiums may not only improve our economic understanding of relevant factors, it is also promising for the improvement of trading strategies. As our results show, signals based on model-implied term premiums seem to work best if they are relatively stable over time. Thus, it is likely that slope and curvature strategies could be further improved by incorporating time-varying

[8]The premiums arising from these two kinds of demand are the main topic of Kang, Rouwenhorst, and Tang (2020).

premiums that reflect short-term supply and demand conditions. The design of such trading strategies is a challenging task for future research.

3.7 Appendix

3.7.1 Expected Futures Returns in the N-factor Model

To prove Equation (3.1), we need to determine $F_{t,T}$ and $E_t(F_{t+h,T})$ under the N-factor model. According to Equation (17) in Cortazar and Naranjo (2006), the price $F_{t,T}$ equals[9]

$$F_{t,T} = \exp\left(x_1(t) + \sum_{i=2}^{N} e^{-\kappa_i(T-t)} \cdot x_i(t) + A(T-t)\right), \tag{3.5}$$

where $x_1(t), \ldots, x_N(t)$ are the time t values of the N stochastic factors and the function $A(T-t)$ equals

$$\begin{aligned} A(T-t) &= (\mu - \lambda_1) \cdot (T-t) - \sum_{i=2}^{N} \frac{1-e^{-\kappa_i(T-t)}}{\kappa_i} \cdot \lambda_i + \frac{1}{2}\sigma_1^2 \cdot (T-t) \\ &\quad + \sum_{i=2}^{N} \sigma_i \sigma_1 \rho_{i1} \frac{1-e^{-\kappa_i(T-t)}}{\kappa_i} + \frac{1}{2}\sum_{i=2}^{N}\sum_{j=2}^{N} \sigma_i \sigma_j \rho_{ij} \frac{1-e^{-(\kappa_i+\kappa_j)(T-t)}}{\kappa_i+\kappa_j}. \end{aligned}$$

In the above expression, μ is the drift rate (under the physical measure) of the Brownian motion process that governs the first factor, σ_i, $i = 1, \ldots, N$, denote the diffusion coefficients of the N factors and $\rho_{ij}, i, j = 1, \ldots, N$, the corresponding instantaneous correlations.

According to the pricing equation, the futures price at time $t+h$ equals

$$F_{t+h,T} = \exp\left(x_1(t+h) + \sum_{i=2}^{N} e^{-\kappa_i(T-t-h)} \cdot x_i(t+h) + A(T-t-h)\right). \tag{3.6}$$

From the perspective of time t, the futures price in Equation (3.6) is a random variable, and our task is to calculate the time t expectation of this random variable under the physical measure. Because all N factors follow either a Brownian motion or an Ornstein-Uhlenbeck process, the term inside the exponential is a weighted

[9] Note that Cortazar and Naranjo (2006) define the log spot price at time t as the sum of the factors plus the drift rate of the first factor times t. For simplicity, we follow Schwartz and Smith (2000), who define the log spot price at time t just as the sum of the factors. These differences in notation do not change the resulting characterization of the expected futures returns.

sum of N normally distributed random variables $(x_1(t+h), \ldots, x_N(t+h))$, plus a non-stochastic term $(A(T-t+h))$. Thus, $F_{t+h,T}$ is log-normally distributed. The expectation of this log-normal random variable is just the exponential of

$$E_t\left(x_1(t+h) + \sum_{i=2}^{N} e^{-\kappa_i(T-t-h)} \cdot x_i(t+h) + A(T-t-h)\right)$$
$$+\frac{1}{2}Var_t\left(x_1(t+h) + \sum_{i=2}^{N} e^{-\kappa_i(T-t-h)} \cdot x_i(t+h)\right). \tag{3.7}$$

Calculation of the expectation and variance from Equation (3.7) under the assumed factor dynamics and collecting terms delivers

$$\begin{aligned} E_t(F_{t+h,T}) \quad = \quad \exp\Bigg(& x_1(t) + \lambda_1 \cdot h + \sum_{i=2}^{N} e^{-\kappa_i(T-t)} \cdot x_i(t) \\ & + \sum_{i=2}^{N} \lambda_i \cdot g(\kappa_i, T-t, h) + A(T-t)\Bigg). \end{aligned} \tag{3.8}$$

Finally, dividing the expression on the right hand side of Equation (3.8) by the expression on the right hand side of Equation (3.5) provides Equation (3.1).

3.7.2 Long- and Short-term Contracts: Limiting Cases

To determine the annualized expected futures returns for some limiting cases, we use Equation (3.4), which is repeated below as Euqation (3.9):

$$\frac{E_t\left(\frac{F_{t+h,T}}{F_{t,T}}\right) - 1}{h} = \frac{\exp\left(\lambda_1 \cdot h + \sum_{i=2}^{N} \lambda_i \cdot g(\kappa_i, T-t, h)\right) - 1}{h}. \tag{3.9}$$

First, consider a "long-term contract", whose maturity date T goes to infinity. In the limit, the functions $g(\kappa_i, T-t, h)$, $i = 2, \ldots, N$, go to zero and expected futures returns converge to

$$\frac{\exp(\lambda_1 \cdot h) - 1}{h}.$$

Now let the holding period h go to zero. Applying L'Hospital's rule on the above expression delivers $\exp(\lambda_1 \cdot h) \cdot \lambda_1$. For $h = 0$, this term equals λ_1. Thus, λ_1 can be interpreted as the annualized simple return of a futures contract with a "very long" time to maturity and a "very short" holding period.

Second, consider a contract with maturity date $T = t+h$. For such a contract, the functions $g(\kappa_i, T-t, h)$, $i = 2, \ldots, N$, take the form $(1-exp(-\kappa_i \cdot h))/\kappa_i$. Therefore, Equation (3.9) becomes

$$\frac{E_t\left(\frac{F_{t+h,t+h}}{F_{t,t+h}}\right) - 1}{h} = \frac{\exp\left(\lambda_1 \cdot h + \sum_{i=2}^{N} \lambda_i \cdot (1 - exp(-\kappa_i \cdot h))/\kappa_i\right) - 1}{h}. \qquad (3.10)$$

For $h \to 0$, both numerator and denominator on the right hand side of Equation (3.10) go to zero. Applying L'Hospital's rule finally delivers a limiting value of $\sum_{i=1}^{N} \lambda_i$. Thus, the sum of all lambda parameters can be interpreted as the annualized simple return of a futures contract with a "very short" time to maturity and a "very short" holding period.

4 Short Term Commodity Futures Contracts: Trading Patterns and Returns

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Abstract

Commodity futures markets are special when compared to equity or bond markets. The trading activities in commodity futures, especially in the last month, are potentially influenced by the physical delivery process, which is unique to commodities. Many research articles try to avoid these problems by excluding the last trading month in their analysis. In this paper we want to analyze the trading patterns in volume, open interest and price during the last months of trading. We find that trading activity is impacted by differences in the timing of the notice period between different commodities. We show that the notice day is the most important day within the lifespan of a commodity futures contract. The notice day presents an important turning point, when a commodity futures contract turns from a very actively traded contract into a rather illiquid contract. Furthermore, we also find that long investors can earn a premium for the risk of having to take physical delivery. We also find, that long-term active month gold contracts show a much a higher trading volume compared to short-term non-active month contracts.

JEL Classification: G11
Keywords: commodity futures, trading activity, delivery process, risk premium

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Short Term Commodity Futures Contracts: Trading Patterns and Returns

4.1 Introduction

Commodity futures markets have become an increasingly popular topic in theoretical and especially in empirical research. However, an aspect that is often neglected in the empirical research on commodity futures is the trading activity in the last weeks of a commodity futures contract. Probably the main reason for this is the delivery process for deliverable commodity futures. Physical delivery is usually unwanted by financial investors and therefore avoided. For example, for investment strategies investors are usually assumed to roll over their long or short position into more distant futures contracts before the delivery process starts. This is done to eliminate possible price effects or illiquidity due to the delivery process. At the same time it also raises the question what exactly is happening with regard to trading volume, open interest and prices during the delivery time period? Are all commodity futures created equal with regard to the delivery process? Or are there differences between different commodities and even between contracts of the same commodity?

While some answers to these questions might be well-known by traders, they have, to the best of our knowledge, not been analyzed in academia. Research topics which are linked to these questions are the maturity effect of commodity futures and the optimization of rolling strategies for investment purposes.

The maturity effect refers to the inverse relationship between the futures volatility and the time to maturity. Samuelson (1965) first illustrated this relationship from his theoretical model. Hence, it is also known as the Samuelson Hypothesis. There is a relatively large body of literature that contributes to this. Empirical studies mostly supported the Samuelson Hypothesis. For example Bessembinder et al. (1997), Galloway and Kolb (1996) or Duong and Kalev (2008) find that the Samuelson Hypothesis holds for agricultural futures and energy futures. At the same time other assets such as metals or financial futures show a weaker or no maturity effect. Brooks and Teterin (2020) find that previously unarbitraged agricultural futures markets now also show periods of stronger arbitrage and a weakened or even absent maturity effect at the same time. They conclude that arbitrage, which requires sufficient commodity inventory levels, reduces the maturity effect. Hence, the maturity effect is negatively correlated with inventory levels.

The rolling strategy is an important part of any commodity futures investment strategy. Investors constantly have to roll over their position, if they want to stay invested. Since the introduction of passive investing in commodity futures via for example the S&P GSCI Index, many investors are replicating this index and its unique rolling strategy. The index roll period is the 5th to 9th business day of each month. During this period the index rolls with an equal weight of 20% per day from the second nearest contract to the third nearest contract. Mou (2011) shows that investors would have earned a significantly higher return of 3.59% from 2000-2009 if they were front-running the index roll-period. This effect was absent in commodities which were not included in the S&P GSCI. It shows the importance of the trading activities in commodity futures contracts leading up to maturity.

In our analysis we want to focus on the trading activities in the last four months before maturity. We will show that not all commodity futures are traded in the same way due to subtle differences in the delivery terms of each contract. We will also look at the differences between so-called active month and non-active month contracts in gold. In Section 2 we will explain the commodity futures delivery process in more detail for different types of commodities. Section 3 describes the dataset, which is used in our empirical analysis. In Section 4 we will look into the trading activities in the last four month before maturity. We are using descriptive statistics and regression models to analyze patterns in monthly returns, trading volume and open interest. Section 5 will summarize the results and give an outlook.

4.2 The Commodity Futures Delivery Process

Most commodity futures contracts have an embedded mechanism for physical delivery. Being able to settle a commodity futures contract via physical delivery is a very important mechanism which also ensures that futures prices and spot prices converge. Without physical delivery, commodity futures markets could potentially decouple from their respective physical counterparts. This section describes the commodity futures delivery process for CME traded commodity futures. Understanding this process is crucial to understanding the behavior of market participants in commodity futures markets. The rules of the delivery process are set in Chapter 7 of the CBOT Rulebook (CME Group, 2021a).

As a contract is nearing its maturity, short and long position holders must prepare to go through the physical delivery process. This delivery process is typically avoided by financial investors (Miffre, 2016). The delivery process typically includes three important periods. The first period is the position period. Starting with the first position day, holders of short positions can indicate their intention to make physical delivery to the clearing house. At the same time all brokers must report open long positions to the clearing house. This information is needed to match the counter parties for the physical delivery. It is important to note that short holders have the right to indicate their intent to make physical delivery. Additionally, the short can also choose the date when he makes his intention to make physical delivery. This day does not have to be the first position day. The position period typically spans over a couple of weeks and ends with the last position day. After the last position day the clearing house will no longer accept intentions to make physical delivery.

The second period, the notice period is often overlapping with the position period. The first notice day is typically the day after the first position day. After the short holder has made his intent to make physical delivery to the clearing house, the clearing house will match this intent with the holder of a long position, who then has to take physical delivery. Long positions are ranked according by the time they have been open. The oldest long position available will be matched with the first short position that gave the intent to make physical delivery. The first notice day usually is the deadline when financial investors no longer want to have an exposure to the commodity futures contract. Starting on the first notice day, they are running the risk of having to accept the physical delivery.

The third and last period in the delivery process is the delivery period. The futures exchange also determines the first and last possible delivery day. On the delivery day the long holder makes the payment to the clearing house and receives the shipping or warehouse certificate. The short holder receives the payment from the clearing house. The former long holder can now decide to store the commodity, deliver the goods to another place or sell the shipping certificate to someone else. If his intention was to hold the futures contract as a financial investment he might be uncomfortable with handling the physical asset at this point.

According to the delivery process, holding a short futures contract during the position period also provides an option of physical delivery. The short holder can decide whether he wants to make use of this option (e.g. make physical delivery) or buy a long position and avoid physical delivery. At the same time the long holder is in the position of an option writer in this context. He has to accept the physical delivery once he is getting the notice from the clearing house. We can expect financial investors to avoid this position.

The timing of the three periods in the delivery process differs between different commodities. For example in energy futures (e.g. NYMEX WTI Crude Oil or NYMEX Natural Gas) the delivery process starts after the last trading day (CME Group, 2021c). The position period and notice period are only one day each and then followed by a one month delivery period. Hence, in energy futures the position and notice period does not directly interfere with an actively traded futures contract. An example for the August 2021 contract is given in Table 4.1. While the last trading day is the 20th of July, the position day is the 21th of July and the notice day is the 22th of July. The both parties than agree on a delivery date in August.

Table 4.1: Position Period, Notice Period and Delivery Period for August 2021 Futures Contracts

			Crude Oil	Gold	Corn
	Contract		Aug 2021	Aug 2021	Sep 2021
First	Trading	Day	23.11.2015	30.09.2019	17.12.2018
Last	Trading	Day	20.07.2021	27.08.2021	14.09.2021
First	Position	Day	21.07.2021	29.07.2021	30.08.2021
Last	Position	Day	21.07.2021	30.08.2021	15.09.2021
First	Notice	Day	22.07.2021	30.07.2021	31.08.2021
Last	Notice	Day	22.07.2021	30.08.2021	15.09.2021
First	Delivery	Day	01.08.2021	02.08.2021	01.09.2021
Last	Delivery	Day	31.08.2021	31.08.2021	16.09.2021

However, for grains (e.g. CBOT Corn) and metals (e.g. COMEX Gold) the situation is different. For grains the position period usually starts around two weeks before the last trading day (CME Group, 2021d). The notice period starts one day after the first position day. Position and notice period end with the last trading day. The delivery period starts one day after the first position day and ends one day after the last trading day. For grains the last two weeks of the nearest futures contract are directly influenced by the physical delivery process. Market participants have to deal with the possibility of physical delivery. The short holder will have the option of physical delivery and the long will have to accept physical delivery once he gets notice from the clearing house. An example for September 2021 contract of Corn is also given in Table 4.1. While trading stops at the 14th of September, the position period starts at 30th of August and ends one day after trading ends at the 15th of September. The notice period start at the 31th of August and spans until the 15th of September. The delivery period is from the 1st of September until the 16th September.

For metals (COMEX Gold, COMEX Silver and COMEX Copper) the overlapping of the position and notice period with the actively traded futures contract is even longer. The first position day is the second last trading day in the month before the last trading day (CME Group, 2021b). The first notice day is the day following the first position day and is the last trading day in the month preceding the trading end of the futures contract. The overlapping of the position and notice period in roughly four weeks. Which is quite long compared to two weeks for CME-traded grain futures and no overlapping for CME-traded energy futures. An example for the August 2021 contract of gold can also be found in Table 4.1.

Another distinction between commodity futures contracts is between so-called active month contracts sometimes also called lead month contracts and other non-active month contracts. The active or lead month contract is usually the nearest contract with the shortest time to maturity. The active month contract can be considered as a benchmark contract for each commodity and is often subject to a more complex daily price settlement procedure than other contracts. For metals the distinction between active and non-active contracts is different then for other commodities. There is a special schedule for active months and sometimes the nearest contract is not the active contract. For gold the nearest contract out of the February, April, June, August and December contracts is the active month contract (CME Group, 2022). Gold futures contracts also exist for the other calendar months but these contracts are only set up three month before maturity and will not become active contracts when they are close to maturity. Hence, for gold we can analyze the difference between contracts that can become active month contracts and contracts that will not become active month contracts. The distinction between contracts than will become active month contracts and those that will not is also featured in CME traded silver and copper futures.

4.3 Dataset

In our empirical study we use the CRB Infotech database provided by Barchart. We are using daily closing prices, open interest and trading volume for NYMEX WTI Crude Oil, COMEX Gold and CBOT Corn. With oil, gold and corn we chose some of the most actively traded commodities out of the categories energy, metals and grains. As explained previously, these three categories have a different time schedule for the delivery process, which gives us the opportunity to analyze the differences between them. The exact dates and contracts of our datasample can be taken from 4.2.

Table 4.2: Datasample

	Crude Oil	Gold	Corn
Trading Symbol	NYMEX:CL	COMEX:GC	CBOT:C
Start Date	22.08.1985	22.01.1979	01.07.1959
End Date	28.02.2019	28.02.2019	28.02.2019
First Contract	CL1986N (Jul)	GC1979H (Mar)	C-1959U (Sep)
Last Contract	CL2021Z (Dec)	GC2021Z (Dec)	C-2021Z (Dec)
Last Completed Contract	CL2019H (Mar)	GC2019G (Feb)	C-2019H (Mar)
Volume and Open Interest	01.01.2001	01.01.2001	01.01.2001
Overlap between Notice Period and Trading	none	1 month	2 weeks

Volume and Open Interest is only available from 01.01.2001 in the CRB Infotech database. We calculate monthly log returns for all available futures contracts using Formula 4.1.

$$r_{i,t} = \log F_{i,t+1} - \log F_{i,t} \tag{4.1}$$

$F_{i,t}$ is the futures price of commodity i at time t and $F_{i,t+1}$ is the futures price at time t+1. Our monthly time interval always spans from the last trading day of a contract to the last trading day of the next contract. We do so in order to have a consistent time interval and not miss out on the last weeks of trading, which is what we want to focus on. In our analysis we are only focusing on returns of contracts with a remaining time to expiry of up to 12 months. In order to have a complete dataset of futures returns for every commodity and month we also use linear interpolation to calculate synthetic prices for non existing contracts. Gold and corn do not have a futures contract for each month in a given year. So we opted to use Formula 4.2 to fill up missing contracts. To determine the price for a missing contract F_{i,t,t_R}, we use the prices of the previous ($F_{i,t,t_{prev}}$) and next contract ($F_{i,t,t_{next}}$).

$$F_{i,t,t_R,syn} = F_{i,t,t_{prev}} * \frac{t_R - t_{prev}}{t_{next} - t_{prev}} + F_{i,t,t_{next}} * \frac{t_{next} - t_R}{t_{next} - t_{prev}} \tag{4.2}$$

It is important to note, that these synthetic prices are indeed prices, that an investor can actually pay (or receive for a short position), if he decides to buy both contracts with the weights used in the interpolation. Following this logic, investors can also earn the returns linked to these synthetic prices. Hence, we decided to include the synthetic prices and returns in our analysis. However, synthetic prices are not calculated for the last month, because there is no previous contract with a shorter time to expiry available for the interpolation. We do not use any method of extrapolation.

Trading volume and open interest is reported in number of contracts. In our analysis we will use the trading volume which is the total number of traded contracts over a given time period (e.g. one week or one month). We are neither using interpolation for trading volume nor for open interest, because there is no appropriate way to do this.

4.4 Analysis of Returns of Short-Term Contracts

In this section we want to focus on the return analysis and link them to the difference in the time schedule for the delivery process. All futures returns have been grouped by the remaining time to expiry. For example the returns for a remaining time to expiry of 1/12 are the returns for all available contracts of a specific commodity with one month left to expiry. We will also call these contracts one-month-contracts, two-month-contracts and so on. The summary statistics can be found in Table 4.3.

In our crude oil dataset the returns are generally positive with a mean monthly log return between 0.39% and 0.61%. The futures returns are highly volatile and the average positive returns are small compared to the standard deviation, which is between 6.83% and 10.41%. The average return is mainly flat for a varying time to expiry. If anything, the returns for a longer time to expiry are slightly higher than for a shorter time to expiry. Importantly, we cannot see a significant difference between the last month to expiry and the other months. In contrast to the mostly flat structure of mean returns, the volatility is clearly increasing for a shorter time to expiry. In Table 4.3 we can clearly see the characteristic decline in volatility. Hence, we can confirm the Samuelson Hypothesis and the results of Bessembinder et al. (1997), Galloway and Kolb (1996), Duong and Kalev (2008) and Kang et al. (2020), who also found the Samuelson Hypothesis to hold for energy futures.

After all we were not surprised to find a mainly flat futures return structure for crude oil, because the delivery process does not overlap with the trading activity. A futures trader in crude oil does not have to worry about physical delivery, because the first notice day is after the last trading day. Hence, there should be no reason for a sudden change in the returns and trading activity in the last month.

For gold the mean monthly log returns across the one-month to two-month-contracts are between -0.05% and 0.33% (Table 4.3). Whereas the term structure was almost flat for oil, gold clearly shows a higher mean return for the last month. The difference between 0.33% for a one-month contract and -0.03% for a two-month contract might not sound like a big difference, but given that commodity futures investments can be scaled easily and long and short position can be used to reduce risk, it would present an attractive opportunity for investors. However, earning this return would not be easy for financial investors, because in gold futures the holder of a long position bears the risk of a physical delivery in the last four weeks of trading. We argue that the incrementally higher return in the last trading month is a risk premium for long holders, who are compensated for a potentially unwanted physical delivery.

The standard deviation of gold futures returns is pretty similar across all contracts. So we cannot confirm the existence of the Samuelson Hypothesis in gold futures. This finding is consistent with Duong and Kalev (2008) and Brooks and Teterin (2020), who also found a flat structure of futures volatility.

The results of monthly log corn futures returns are similar to gold. The mean monthly log returns range between -0.82% and -0.10% (Table 4.3). The one-month-contract shows the highest mean log return of -0.10%, while the two-month (-0.45%) and three-month-contracts (-0.81%) are lower. In corn futures the delivery process also overlaps with trading activity in the last two weeks, so we also argue that the difference is a risk premium for long holders in the last two weeks of trading.

Contrary to gold, corn monthly futures log returns show a clear pattern of decreasing volatility for contracts with a longer time to expiry. This is also consistent with previous results from Brooks and Teterin (2020) who found a downward sloping futures volatility structure for agricultural commodities.

In summary our return analysis points to the direction that an overlapping delivery process leads to a risk premium for long holders. Commodity futures with no overlapping of the delivery process and trading, like crude oil, do not provide a higher return in the last trading month, whereas commodities with an overlapping delivery process such as gold or corn show a remarkable high return of the one-month contract. In the next subsection we complement our return analysis by looking into the trading activity measured by trading volume and open interest.

Table 4.3: Summary Statistics of Commodity Futures Returs

Time to Expiry	n	min	Q_1	mean	Q_2	Q_3	max	σ
Crude Oil								
1/12	392	-0.4336	-0.0547	0.0039	0.0115	0.0728	0.3480	0.1041
2/12	392	-0.4110	-0.0510	0.0043	0.0101	0.0696	0.3407	0.0960
3/12	392	-0.4038	-0.0472	0.0050	0.0118	0.0677	0.3129	0.0916
4/12	392	-0.3977	-0.0414	0.0054	0.0120	0.0640	0.3011	0.0877
5/12	392	-0.3924	-0.0380	0.0057	0.0120	0.0614	0.2922	0.0844
6/12	392	-0.3865	-0.0360	0.0059	0.0118	0.0575	0.2847	0.0815
7/12	392	-0.3809	-0.0334	0.0059	0.0112	0.0541	0.2788	0.0790
8/12	392	-0.3753	-0.0311	0.0059	0.0106	0.0523	0.2750	0.0769
9/12	390	-0.3697	-0.0303	0.0055	0.0110	0.0510	0.2737	0.0751
10/12	384	-0.3640	-0.0307	0.0046	0.0091	0.0480	0.2744	0.0735
11/12	376	-0.3581	-0.0277	0.0061	0.0088	0.0475	0.2750	0.0711
12/12	363	-0.3521	-0.0258	0.0055	0.0080	0.0450	0.1910	0.0683
Gold								
1/12	479	-0.2310	-0.0246	0.0033	0.0003	0.0278	0.2402	0.0521
2/12	479	-0.2318	-0.0290	-0.0003	-0.0026	0.0249	0.2274	0.0522
3/12	479	-0.2319	-0.0296	-0.0005	-0.0025	0.0247	0.2301	0.0524
4/12	477	-0.2319	-0.0296	-0.0004	-0.0026	0.0246	0.2323	0.0526
5/12	478	-0.2327	-0.0295	-0.0005	-0.0024	0.0246	0.2344	0.0526
6/12	476	-0.2333	-0.0295	-0.0005	-0.0023	0.0246	0.2371	0.0527
7/12	477	-0.2339	-0.0285	-0.0005	-0.0023	0.0247	0.2398	0.0527
8/12	475	-0.2344	-0.0284	-0.0006	-0.0025	0.0249	0.2431	0.0528
9/12	476	-0.2349	-0.0283	-0.0005	-0.0018	0.0252	0.2464	0.0528
10/12	474	-0.2354	-0.0283	-0.0006	-0.0022	0.0250	0.2490	0.0528
11/12	475	-0.2358	-0.0278	-0.0005	-0.0019	0.0248	0.2514	0.0529
12/12	473	-0.2363	-0.0281	-0.0005	-0.0020	0.0246	0.2526	0.0529
Corn								
1/12	300	-0.3262	-0.0394	-0.0010	-0.0024	0.0344	0.5546	0.0741
2/12	300	-0.2968	-0.0399	-0.0045	-0.0064	0.0311	0.3976	0.0697
3/12	300	-0.2670	-0.0415	-0.0081	-0.0083	0.0275	0.3739	0.0676
4/12	300	-0.2367	-0.0414	-0.0082	-0.0088	0.0244	0.3761	0.0666
5/12	299	-0.2278	-0.0412	-0.0079	-0.0090	0.0242	0.3783	0.0661
6/12	300	-0.2189	-0.0401	-0.0070	-0.0082	0.0231	0.3805	0.0655
7/12	299	-0.2102	-0.0382	-0.0066	-0.0077	0.0218	0.3729	0.0643
8/12	299	-0.2068	-0.0372	-0.0060	-0.0076	0.0213	0.3655	0.0629
9/12	299	-0.2036	-0.0354	-0.0058	-0.0058	0.0202	0.3581	0.0616
10/12	296	-0.1998	-0.0333	-0.0050	-0.0058	0.0210	0.3483	0.0601
11/12	278	-0.1960	-0.0339	-0.0055	-0.0069	0.0213	0.3385	0.0603
12/12	231	-0.1922	-0.0330	-0.0064	-0.0057	0.0207	0.3265	0.0560

4.5 Analysis of Trading Volume and Open Interest of Short-Term Contracts

In this section we want to look at the trading activity in the last months to expiry in more detail. We are particularly interested to spot differences between the selected commodities in trading volume and open interest caused by the delivery process and the first notice day.

Figure 4.1 presents the monthly trading volume for crude oil. This is the average sum of all traded contracts in one month. Crude oil futures are clearly more liquid for a shorter time to expiry. Generally speaking the less time to expiry is left the more actively the contract is traded. The median amount of traded contract is around 5 million for the one-month contract, around 2.5 million for the two-month contract and decreasing further for more distant contracts. In Figure 4.2 we are zooming in on the trading activity by splitting up the trading volume into weeks. Crude oil shows an equal distribution of trading volume during the last four weeks of trading. Even in the last week leading up to expiry the futures contract is still very actively traded. There is no visible cut, when trading starts to slow down in a crude oil contract.

Figure 4.1: Monthly Trading Volume of Crude Oil

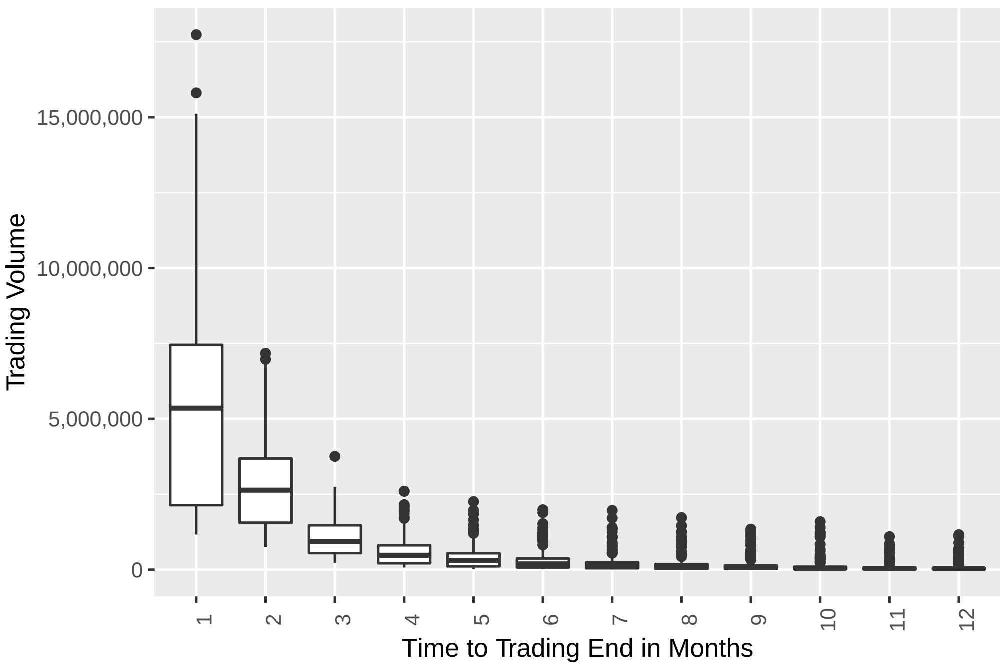
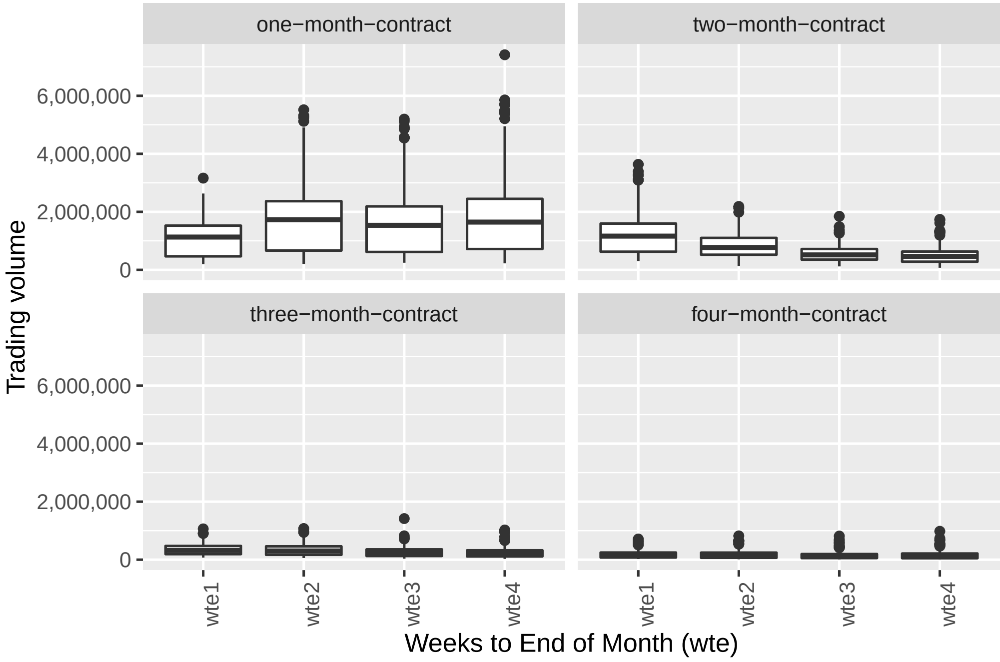


Figure 4.2: Weekly Trading Volume of Crude Oil



In addition to the trading volume we also want to look at the change of open interest and the relationship between the change of open interest and the trading volume. Figure 4.3 plots the weekly change in open interest for the four contracts closest to maturity. We can see that crude oil open interest is increasing in the two-month, three-month and four-month contract. The increase is particularly high in week one and week two of the two-month contract. In the one-month contract traders are reducing their open interest. The majority of open interest is closed out in the last two weeks. This gives us an indication that traders are rolling over their positions from the one-month to the two-month contract.

Figure 4.4 plots the change in open interest against the trading volume on a weekly basis. A higher trading volume clearly correlates with a higher reduction in open interest. The plot also indicates that many investors roll their exposure from the one-month to the two-month contract.

Figure 4.3: Weekly Change in Open Interest of Crude Oil

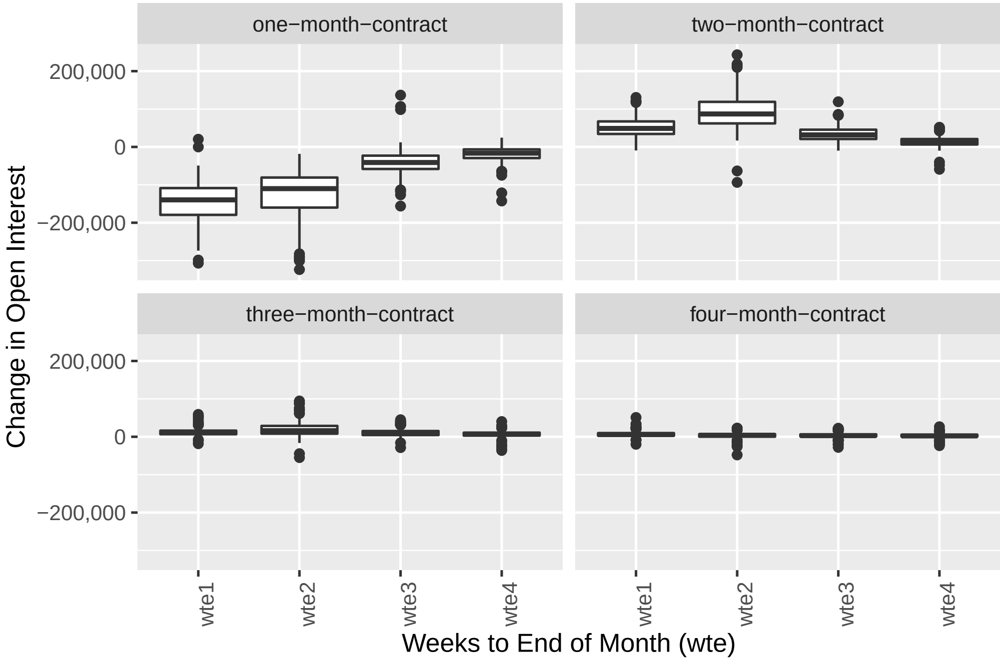
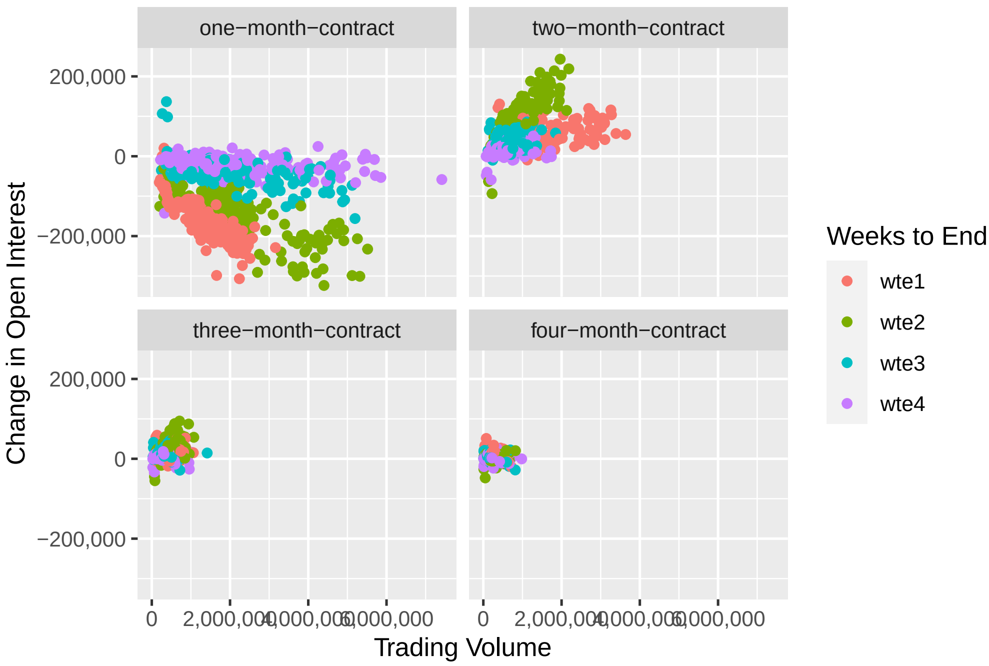


Figure 4.4: Scatter Plot of Trading Volume and Change in Open Interest of Crude Oil



In contrast to crude oil, gold shows different patterns in trading volume and open interest. Figure 4.5 shows the distribution of trading volume grouped for monthly contracts. The trading volume is highest for the three-month contract. Contrary to crude oil the trading volume in the one-month contract is very low. In the weekly breakdown in Figure 4.6 we can see that the one-month contract basically becomes illiquid in the last three weeks until expiry. These findings go hand in hand with the first notice day being about four weeks before the last trading day for gold. After the notice day financial investors are not interested in trading the futures contract. At the same time the premium we discovered in the return analysis is also difficult to earn because the contract will not be traded very actively after the notice day.

The distinction between active month contracts and other non-active contracts for gold also gives us the opportunity to compare these two categories. The non-active contracts are only set-up by the Futures Exchange three months before maturity. Figure 4.7 and Figure 4.8 show the trading volume and the open interest during the last four months. We can clearly see that trading volume is very low for non-active contracts compared to active contracts. The open interest also remains largely unchanged for non-active contracts. In other words there is no build up of open interest which is then reduced as the contract approaches the notice period. For active contracts we can see a build up four months before expiry and a substantial reduction two months before expiry.

Figure 4.9 and 4.10 support our findings for gold. The open interest is almost entirely closed in the last week of the two-month contract. Not surprisingly investors try to avoid the physical delivery and cancel out their open interest before the notice period. At the same time Figure 4.10 indicates that investors tend to roll their exposure from the two-month to the four-month contract. The red dots marking the reduction in open interest in week one of the two-month contract coincide with an increase in open interest in week one of the four-month contract.

To further test the significance of the drop in trading volume after the notice day, we also regressed the weekly trading volume and the change in open interest on a constant and an indicator variable, which is one if the trading week is after the notice day and zero otherwise. The results are stated in Table 4.4. In this analysis we can see a very significant negative coefficient of $(-326,680)$ for the notice day indicator variable for the trading volume. The notice day effect almost entirely offsets the positive constant of $(349,193)$. This confirms that trading almost comes to a standstill after the notice day for gold. The results for open interest are different. Open interest generally reduces during the last two months as indicated by the negative constant $(-22,167)$ but after the notice day this effect is almost entirely offset $(18,341)$ because there is only a small number of open contracts remaining.

Figure 4.5: Monthly Trading Volume of Gold

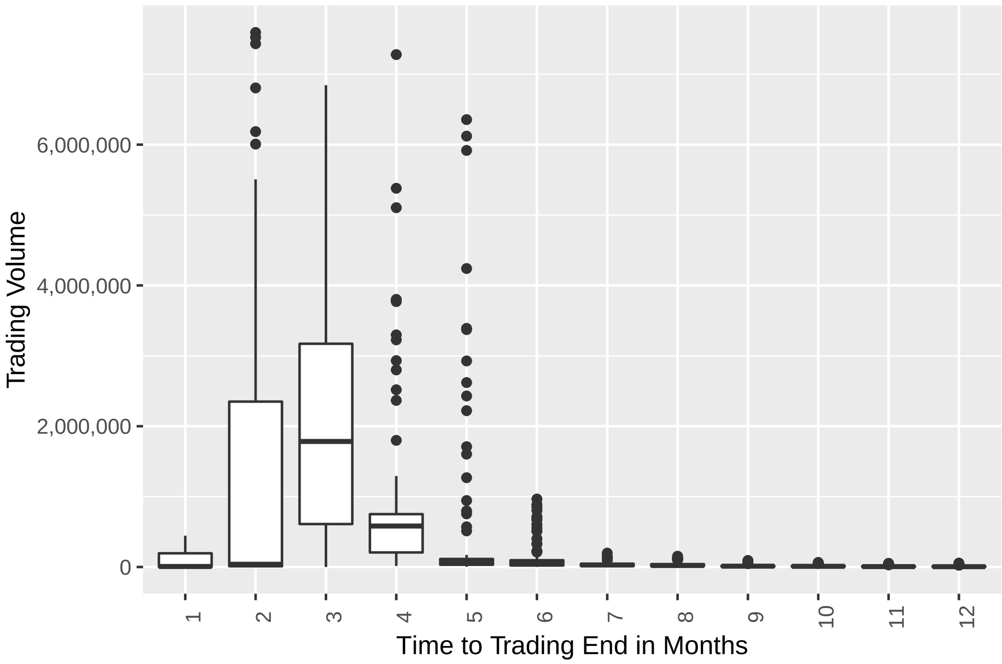


Figure 4.6: Weekly Trading Volume of Gold

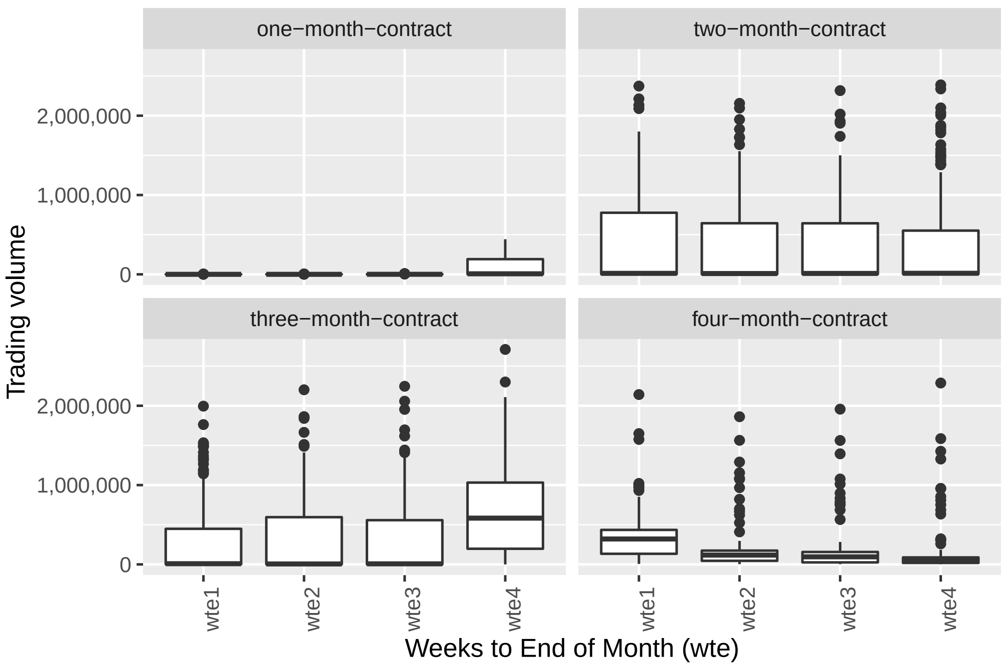


Figure 4.7: Trading Volume for Active and Non-Active Contracts

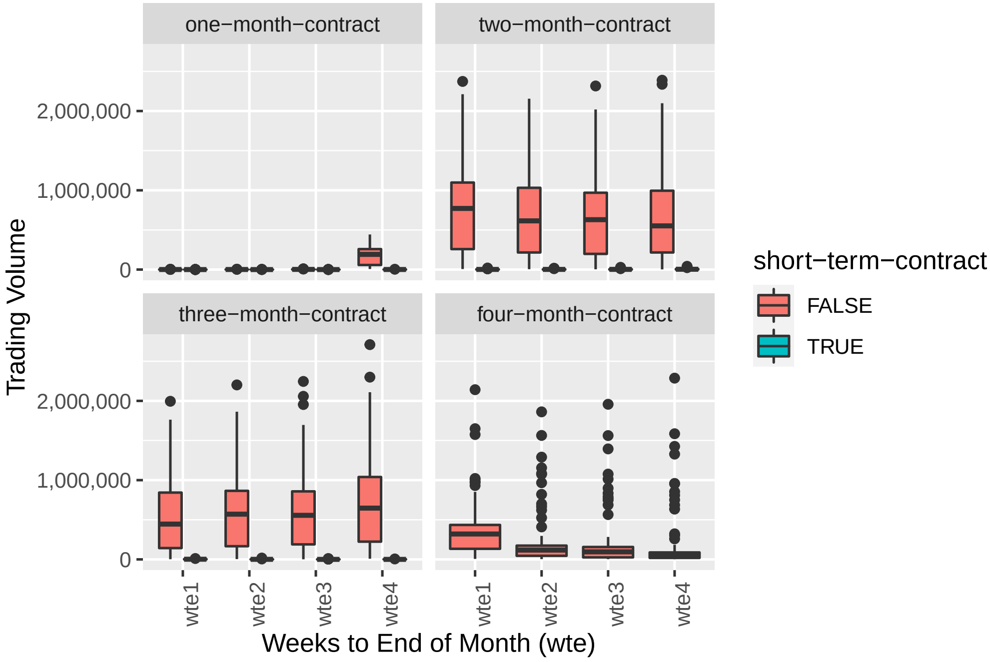


Figure 4.8: Open Interest for Active and Non-Active Contracts

Table 4.4: Trading Volume Regression with Notice Day Dummy Variable (Gold)

	Dependent variable:	
	Weekly Trading Volume	Change in Open Interest
	(1)	(2)
Constant	349,193***	-22,167***
	(12,718)	(1,083)
After notice day	-326,680***	18,341***
	(17,987)	(1,532)
Observations	1,742	1,742
R^2	0.159	0.076
Adjusted R^2	0.159	0.076
Residual Std. Error (df = 1740)	375,368.000	31,976.680
F Statistic (df = 1; 1740)	329.853***	143.284***

Note: This table shows the regression results for a model where the weekly trading volume and the change in open interest is regressed on a constant and an indicator variable for the notice day. The notice day variable is zero before the notice day and one after the notice day. Standard errors are stated in parentheses.

Figure 4.9: Weekly Change in Open Interest of Gold

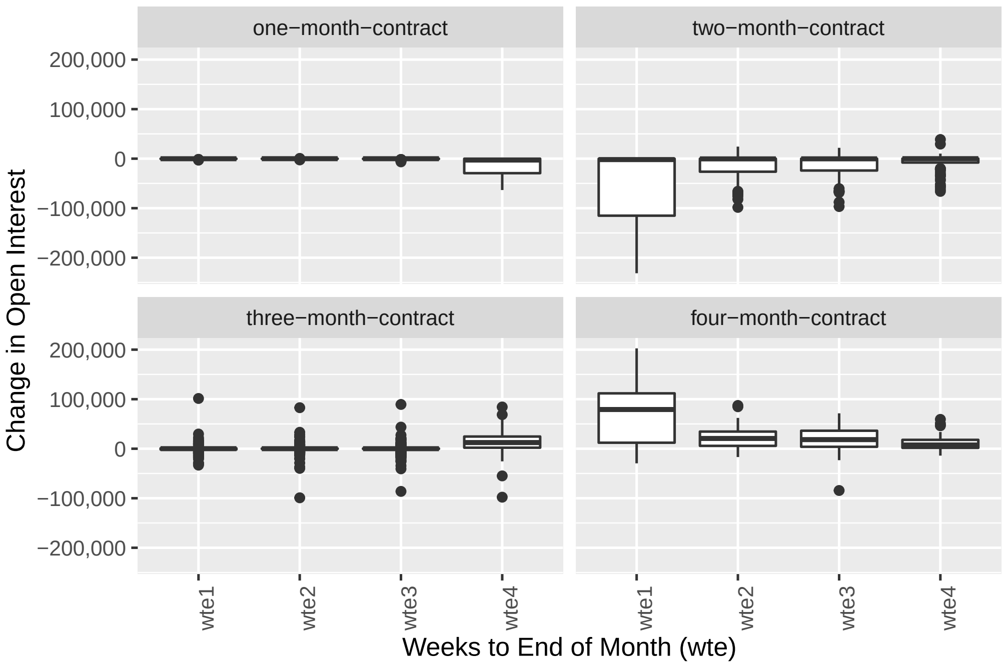
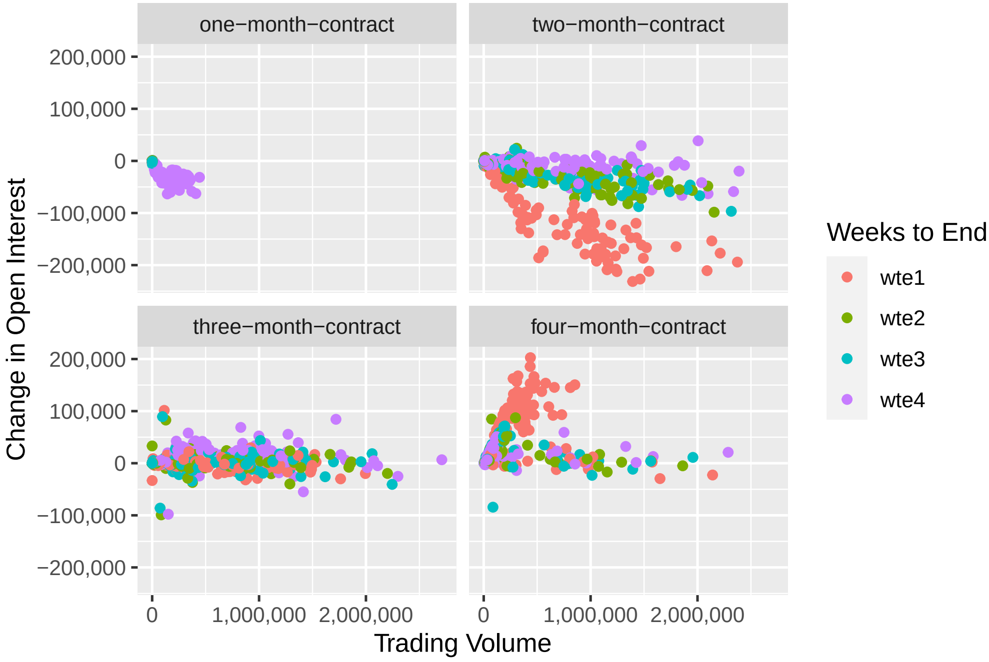


Figure 4.10: Scatter Plot of Trading Volume and Change in Open Interest of Gold



The results for corn are inline with our previous findings for gold. The trading volume is relatively high until two weeks before expiry of the contract (Figure 4.12). In general the trading volume is high for every month up to six months. After this trading activity gradually tapers down (Figure 4.11). Especially the sharp drop in trading volume two weeks before expiry shows the importance of the delivery process and the first notice day in particular. The first notice day is two weeks before expiry for corn. After the notice day trading activity is reduced to a minimum. The pattern overall looks similar to gold, except that they are shifted by two weeks towards the expiry date.

The sharp drop in open interest two weeks before expiry (Figure 4.13) also illustrates the importance of the first notice day. The reduction in open interest precedes the drop in trading activity. After the reduction of the open interest the contract becomes relatively illiquid for the remaining two weeks. Figure 4.14 shows that corn traders preferably roll their exposure from the one-month contract to the three-month contract. The blue and purple dots show that a decrease in open interest in the one-month contract correlates with an increase in open interest in the three-month contract.

Figure 4.11: Monthly Trading Volume of Corn

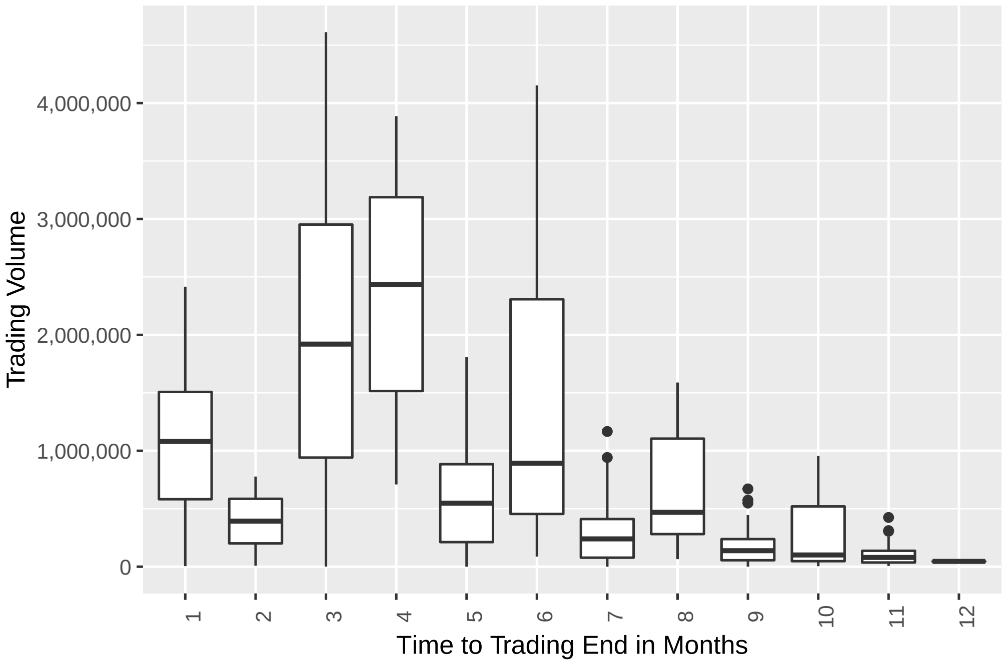


Figure 4.12: Weekly Trading Volume of Corn

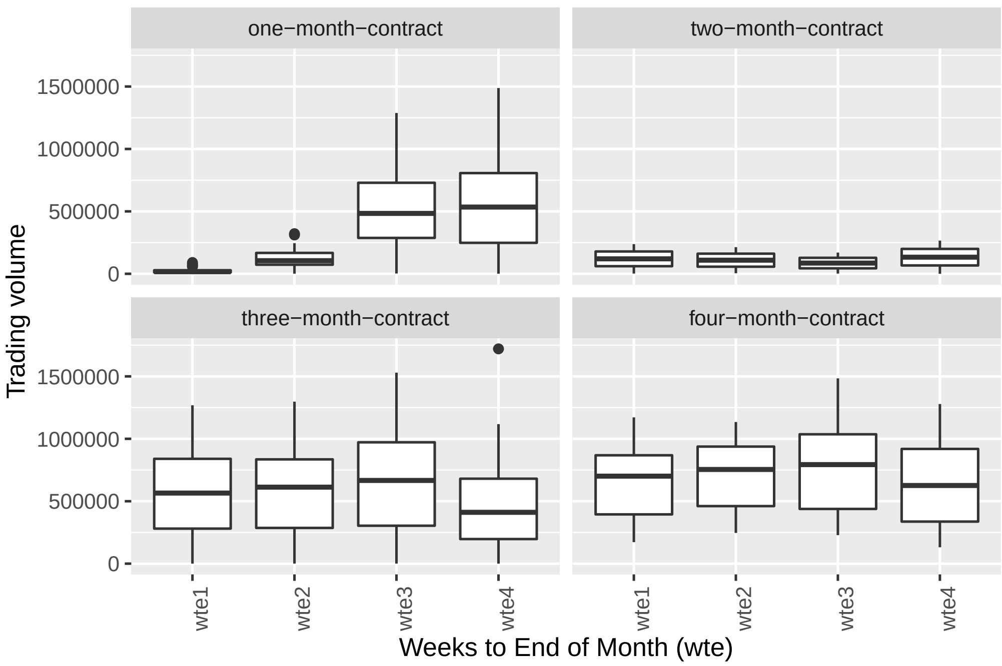


Table 4.5: Trading Volume Regression with Notice Day Dummy Variable (Corn)

	Dependent variable:	
	Weekly Trading Volume	Change in Open Interest
	(1)	(2)
Constant	538,841***	-104,549***
	(17,939)	(3,530)
After notice day	-467,397***	92,208***
	(25,609)	(5,039)
Observations	377	377
R^2	0.470	0.472
Adjusted R^2	0.469	0.470
Residual Std. Error (df = 375)	248,580.400	48,919.050
F Statistic (df = 1; 375)	333.096***	334.751***

Note: This table shows the regression results for a model where the weekly trading volume and the change in open interest is regressed on a constant and an indicator variable for the notice day. The notice day variable is zero before the notice day and one after the notice day. Standard errors are stated in parentheses.

In a regression model with an indicator variable for the notice day we can again confirm that trading activity is greatly reduced after the notice day (Table 4.5). The negative effect after the notice day ($-467,397$) almost offsets the positive constant of $538,841$ for trading volume. After the notice day, the decrease in open interest also almost stops. In both regression models the indicator variable for the notice day is highly significant. These results are very similar to our results for gold.

In summary the analyses of trading volume and open interest for crude oil, gold and corn highlight the importance of the delivery process embedded in commodity futures. Different time schedules for different commodities allow us to clearly spot the differences for crude oil, gold and corn. The beginning of the notice period marks a clear turning point for every commodity futures contract. Before the first notice day, trading volume generally increases towards the expiry date. When the notice day approaches, trading volume remains high but open interest is greatly reduced as traders cancel out their position in order to avoid physical delivery. After the first notice day, trading activity greatly diminishes and the contract becomes relatively illiquid.

Figure 4.13: Weekly Change in Open Interest of Corn

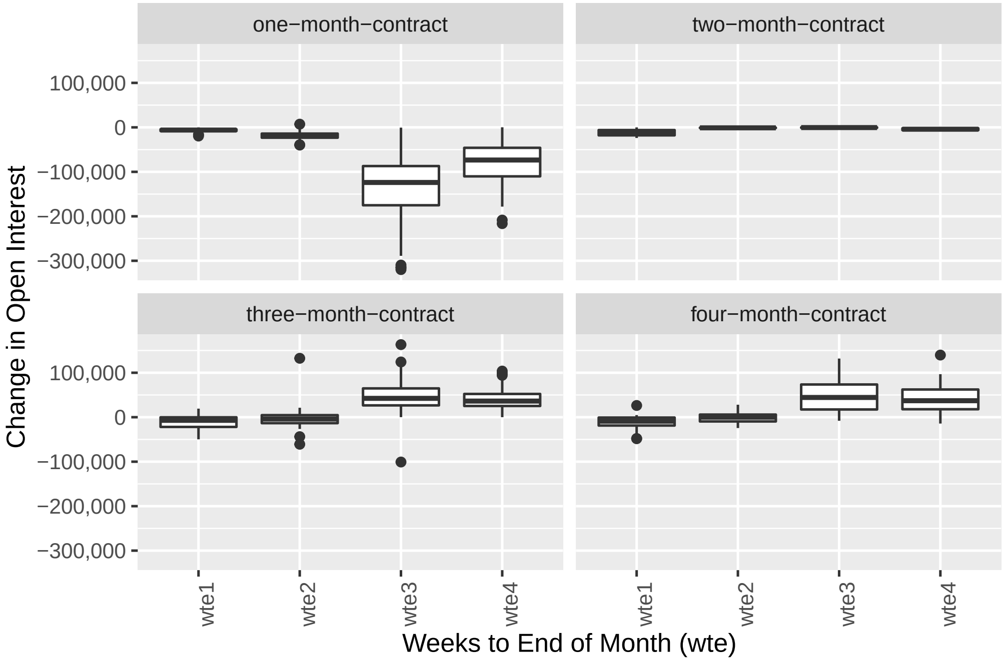
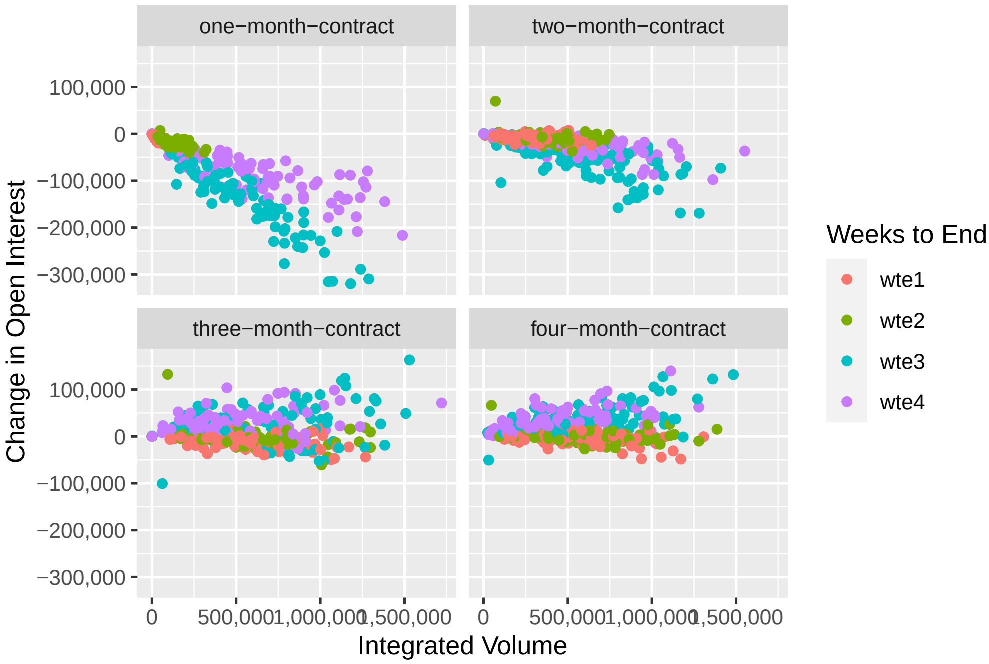


Figure 4.14: Scatter Plot of Trading Volume and Change in Open Interest of Corn



4.6 Conclusion

We studied returns and trading activity during the last months until contract expiry in three major commodity futures. The results clearly show the importance of the delivery process for commodity futures trading.

Firstly, we find a risk premium for long holders of futures contract when there is an overlapping of the notice period with the trading period of a commodity futures contract. Long investors are running the risk of a possible physical delivery which might be unwanted and can be triggered by the short counter party. This premium seems to exist for gold and corn but not for crude oil, because the notice period does not overlap with the trading period for crude oil. Long holders with the ability to cost-efficiently manage a physical delivery can try to earn a risk premium for example in agricultural as well as to some degree in metal commodity futures. However, they will also face some liquidity risks in the last month because trading volume is very limited in the last weeks.

Secondly, in our analysis of gold futures we could see a clear distinction between short-term non-active contracts and long-term active contracts in trading volume and open interest. Short term non-active contracts show a very low trading volume and there is no build up of open interest like there is in long-term active contracts.

Thirdly, the notice day is the single most important day for each commodity future. After the notice day, trading activity and open interest is greatly reduced and the contract becomes relatively illiquid. When looking at the results in becomes obvious that a short term futures contract with two months left to expiry for gold is different to the same futures contract for crude oil. In the case of gold there is effectively one month of active trading left, while the crude oil contract will be actively traded for the full remaining two month. This fact should be taken into account whenever commodity futures are used in empirical studies. After all not all commodity futures are created equal and differences in the timing of the physical delivery process, as well as the distinction between active and non active contracts should be taken into account and are relevant.

5 Conclusion

This thesis has investigated investment strategies, term premiums and trading activities in commodity futures markets. Beginning with an analysis of passive long-only commodity futures trading strategies, followed by a new approach to model the term structure of expected futures returns and finished with an analysis of trading activities in commodity futures before expiry, the thesis has covered multiple important aspects of commodity futures. The findings in this thesis are important to investors, risk-managers, hedgers and producers.

This section aims at summarizing the results and the main contributions this thesis has made to the general discipline.

5.1 Main Results

The research paper *Smart Beta Strategies on Commodity Futures Markets* provides a comprehensive analysis of passive long-only commodity futures investment strategies. The first main result is to find a definition for Smart Beta strategies in commodity futures markets. Smart Beta strategies can be defined as all trading strategies that use a certain weighting principle which offers a reasonable possibility to generate an attractive risk to return profile by exploiting an anomaly or using portfolio optimization techniques. The study then analyzes seven different trading strategies, an equal-weight strategy, two low-volatility strategies, two momentum strategies and two term-structure strategies. All these strategies can be implemented relatively easily by investors.

The second main result is the result from the empirical analysis of the trading strategies and the dominance of the term-structure strategies. The term-structure strategies which invest in commodity futures in backwardation are very profitable with excess returns of up to 25% and a Sharpe ratio of up to 1.17. This result shows us the great value of information from the term structure of commodity futures prices. Furthermore, these returns cannot be explained by known risk-factors from bonds or equities.

The second paper *A Factor Decomposition of Term Premiums in Commodity Futures Markets* models and examines the term structure of expected commodity futures returns. We use the N-Factor Model by Cortazar and Naranjo (2006) to model the term structure of expected commodity futures returns. Focusing on the expected returns we can reduce the number of estimated parameters and improve our estimation. At the same time our model is still arbitrage free and offers flexibility.

A main result is that we can decompose the term structure of expected returns into three latent factors. These factors are a constant, a linear and a non-linear function of the time to maturity. This decomposition is capable of modeling various term structures for different commodities. It is also able to pick up effects from different economic sources such as hedging or liquidity demand. Finally we find that profitable trading strategies can be formed based on our estimated term structure of expected returns.

The third paper *Short Term Commodity Futures Contracts: Trading Patterns and Returns* studies returns and trading activity during the last months until contract expiry in three major commodity futures. We analyzed the possible influence of the delivery process on the trading activities and returns of commodity futures. The results clearly show the importance of the delivery process. We find a risk premium for long holders of futures contract when there is an overlapping of the notice period with the trading period of a commodity futures contract. For example this is the case for metals (gold) or grains (corn). When there is no overlapping like for example for crude oil, there is no such risk premium in the last trading month. However, these premiums might be hard to obtain due to limited liquidity. At the same time the notice day is also a very important day during the lifespan of a commodity futures contract. After the notice day trading activity is greatly reduced and the contract basically relatively illiquid. This should be taken into account carefully, as it varies for different commodities. For example for crude oil the notice period starts after the end of trading, but for gold it is roughly four weeks before the last trading day. Newer empirical studies on commodity futures could use the first notice day as the last day in an empirical analysis, as it marks the end of very active and liquid trading in a commodity futures contract.

5.2 Contributions to the Discipline and Directions for Future Research

The contribution to the discipline can mainly be divided into two areas: The trading strategies literature and literature on the structure of commodity futures markets.

(1) Trading Strategies on Commodity Futures Literature

This thesis provides new and innovative trading strategies for commodity futures. To the best of my knowledge, this thesis is the first to apply the idea of smart beta factor investing to commodity futures. It takes ideas from equity and bond markets and transfers them to commodity futures. Although similar strategies have been discussed before, the framework here is different. All smart beta strategies are very easy to implement and are constructed as long-only passive investment strategies. The very good results for term structure strategies reveal the importance of the term structure of commodity futures.

The second paper analyzes trading strategies based on a model implied term structure of expected returns. This is a novel approach that has, to the best of our knowledge, not been used before. We show that the results can be used to form profitable trading strategies. Future research is needed to explain the fundamental drivers behind the premiums that are earned by investors who follow these strategies.

(2) Structure of Commodity Futures Markets Literature

This thesis also contributes to a better understanding of the structure of the commodity futures market. The second paper uses a novel approach to model the term structure of expected futures returns. The term structure of expected futures returns is an aspect which has been neglected to some degree by prior research. Our new model-based approach is a very flexible way to model the expected return curve of different commodities. The decomposition into a constant, a linear and a non-linear factor is easy to understand and links well to the literature on the term structure of interest rates. Future research should answer to what degree the observed expected return curve is time-varying and how time-varying risk premiums could be implemented. The third paper makes an important contribution on the structure of commodity futures markets. The delivery process of commodity futures influences trading activities in commodity futures. An overlapping of the trading period and the notice periods potentially rewards long investors with a risk premium.

The third paper also highlights the importance of the notice day. After the notice day, trading activity in commodity futures is greatly reduced. The analysis also shows that active month gold futures contracts are traded much more actively than non-active contracts. The market obviously distinguishes between these two different types of contracts.

Finally, the findings of this thesis are also relevant for practitioners in asset management and risk management functions. The trading strategies proposed in this thesis can be an inspiration for investment products and the insights into the market structure and the term structure of expected returns can also be helpful in risk-management applications.

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Statement of contribution
to each paper of the cumulative dissertation

To the three papers of the cumulative dissertation, I personally contributed as follows:

1. to the paper *Smart Beta Strategies on Commodity Futures Markets* (single-author paper): conceptualization, empirical analysis, and writing, in total: 100%,

2. to the paper *A Factor Decomposition of Term Premiums in Commodity Futures Markets* co-authored by Olaf Korn and Stefan Trück: significant contributions to the conceptualization, empirical analysis, and writing, in total: 70%.

3. to the paper *Short Term Commodity Futures Contracts: Trading Patterns and Returns* co-authored by Georg von Kleist: significant contributions to the conceptualization, empirical analysis, and writing, in total: 70%.

Göttingen, 24.02.2022

Place, Date — Marcel Rothenberger

Ph.D. program in Economics
Declaration for admission to the doctoral examination

I confirm

1. that the dissertation "Trading Strategies and Return Patters in Commodity Futures Markets" that I submitted was produced independently without assistance from external parties, and not contrary to high scientific standards and integrity,

2. that I have adhered to the examination regulations, including upholding a high degree of scientific integrity, which includes the strict and proper use of citations so that the inclusion of other ideas in the dissertation are clearly distinguished,

3. that in the process of completing this doctoral thesis, no intermediaries were compensated to assist me neither with the admissions or preparation processes, and in this process,
   - no remuneration or equivalent compensation were provided
   - no services were engaged that may contradict the purpose of producing a doctoral thesis

4. that I have not submitted this dissertation or parts of this dissertation elsewhere.

I am aware that false claims (and the discovery of those false claims now, and in the future) with regards to the declaration for admission to the doctoral examination can lead to the invalidation or revoking of the doctoral degree.

Göttingen, 24.02.2022

Place, Date — Marcel Rothenberger