Trend Following Strategies in Commodity Markets and the Impact of Financialization*

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Abstract

This paper studies the returns to a simple trend following strategy in commodity markets and their potential drivers. We find that the strategy delivers low annualized returns in the period from 1990 to 2004 of 2.1% that show a significant increase from 2005 to 2013 to 6.5%, yielding Sharpe ratios of up to 1.8. This rise in returns coincides with the increase in participation in these markets by financial investors. Commodity markets entail particular features not shared by other assets classes, mainly physical delivery and the non-availability of infinitely lived contracts. For commodity funds that wish to maintain constant exposure, this means that they have to roll their positions to create an infinitely lived asset. This need to roll creates predictable demand for liquidity and predictable steepening and flattening of the futures curve, which can be exploited by trend following strategies. We find that the strategies returns are positively correlated to the rebalancing demand of funds thereby providing indirect evidence of limits of arbitrage in these markets.

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1 Introduction

Investments in commodities have grown at a rapid pace, from \$6 billion in 2000 to over \$300 billion in 2013[1] so that commodities have become an asset class akin to equities or fixed income. As a result commodity futures markets themselves have become financialized in that numerous exchange-traded and other mutual funds have been created to offer investors risk exposure to this asset class. Most of these funds either track the large commodity indices, i.e. the Goldman-Sachs Commodity Index (GSCI) or the Dow Jones-UBS Index (now Bloomberg Commodity Index (BCI)), directly or are benchmarked against them. Rather than buying and storing the physical commodities, funds typically invest in commodity futures. Specifically, much of these funds' trading activity in commodity futures markets is concentrated in calendar spreads.[2]

In this paper, we study the returns to a simple trend-following strategy in calendar spreads in 25 different commodity markets and document a significant increase in the returns to this strategy following 2005. The Sharpe ratio of this strategy on an equal-weighted portfolio of commodities increases from 0.48 during the 1990 to 2004 period to 1.76 during the 2005 to 2013 period, and this increase coincides directly with the rapid growth of long-only investments in commodity markets. These returns are of interest to financial economists for at least three reasons. First, the trading strategy captures a heretofore undocumented impact of financialization by virtue of trading in calendar spreads. Second, the returns can be directly related to the rebalancing needs of commodity mutual funds. Third, we confront these returns with

[1] "Rust-proof," The Economist, November 30th, 2013.

[2] A calendar spread consists of simultaneously buying and selling futures contracts with different maturities but with the same underlying commodity.

many known risk factors, and the returns cannot be explained as a compensation for risk. We apply the same strategy to a control group of commodity futures that are not strongly affected by financialization and find no significant change in the Sharpe ratio following 2005 despite a very comparable development in price levels as shown in Figure 2.

Researchers usually study returns to commodity investing via returns on commodity futures and/or commodity spot prices. Unlike in the equity markets in which it is possible to buy and hold shares of a firm, participation in futures markets always requires a more active approach because there are no infinitely lived futures contracts. As futures come closer to expiry, positions have to be closed to avoid physical settlement. The activity of closing a contract and buying a contract with longer time to maturity is usually referred to as "rolling" or rebalancing. For a large fund, this process has to be actively managed and is not necessarily mechanically related to calendar time. As we detail in Section 3 the rebalancing process is carried out using calendar spreads. This becomes particularly obvious when comparing the amount of noncommercial spreading (as a percentage of open interest) for the commodities that are included in the major indices with the commodities that are not included in the major indices. Figure 2 shows that while the index commodities exhibit a strong increase in spreading following 2005, again coinciding with the increase in assets under management, the off-index commodities show no significant change in spreading.

Given that rebalancing is unavoidable for mutual funds and involves trading calendar spreads, analyzing the behavior of calendar spreads is natural in the context of analyzing the consequences of financialization on commodity markets. We analyze the time series behavior of the returns of calendar spreads and find an increase in autocorrelation for many markets. When we link the coefficient of first order autocorrelation to money managers' positions, we find that on average money managers contribute to an increase in temporal dependence. This increase in autocorrelation is counterintuitive as market access has become less costly through the introduction of electronic trading. Electronic trading naturally invites greater participation, which is typically associated with an increase in liquidity that leads to faster price discovery. This would usually result in less temporal dependence.

If infinite arbitrage capital were available, long-only funds and their rebalancing behavior would not have an effect on the returns of calendar spreads. However, there is by now ample evidence in the literature, e.g. the survey article of Gromb and Vayanos (2010) and the numerous references therein, that arbitrage capital may be "slow moving" and that there exist limits of arbitrage. Empirical findings on limits of arbitrage are often in the context of demand shocks, i.e. large buying or selling activities, such as index inclusions and exclusions or fire sales of mutual funds. Attaining permanent long-only investment in commodities through futures markets entails periodic rebalancing and therefore potentially leads to demand shocks in the securities involved in this process — calendar spreads. This is because in the practical execution of rebalancing, mutual funds sell calendar spreads thereby automatically offsetting their position in the maturing contract and creating a new long position in a contract with longer maturity.

The (calendar spread trading) strategy detailed in the paper generates signals using changes in carry (or the basis) and resembles a time series momentum strategy. We therefore call it *momentum in carry.* As positions in our strategy are taken in calendar spreads, which are heavily employed in the rebalancing process, and the difference in returns to the strategy between the group of index commodities and off-index commodities is large, we understand the results to be supporting the "institutional theory of momentum" of Vayanos and Woolley (2013).

2 Literature Review

Traditionally, futures markets existed as a means of providing insurance for producers and direct consumers of commodities against future price fluctuations. On a simple level, participants in these markets can be classified into producers or direct consumers and speculators. Producers or direct consumers are seeking insurance, which is usually provided by the speculators, who are often assumed to be risk averse and thus demanding a risk premium. This basic intuition is postulated in the theory of normal backwardation of Keynes (1930), Hicks (1939) and Cootner (1960).

Since then, a considerable empirical literature has developed. Dusak (1973) investigates the question of risk premia and Jagannathan (1985) derives pricing of futures contracts and investigates the consumption CAPM. Fama and French (1987) and Gorton, Hayashi, and Rouwenhorst (2012) find that carry, i.e. the difference between the spot and the futures price has predictive power both in the time series and the cross-section. Carry and its use as a cross-sectional return predictor is investigated for many different asset classes by Koijen, Moskowitz, Pedersen, and Vrugt (2013). Our approach is loosely related to theirs. However, rather than using the absolute level of carry, we are concerned with changes in carry relative to a historical level. Our strategy (detailed in Section 4.1) can therefore best be understood as a *momentum in carry* approach. The momentum literature was started by Jegadeesh and Titman (1993), who were only investigating equity markets. More recently, Asness, Moskowitz, and

Pedersen (2013) and Moskowitz, Ooi, and Pedersen (2012) also apply momentum to other asset classes. The work of Moskowitz, Ooi, and Pedersen (2012) is particularly closely connected to ours as our strategy builds on the time series behavior rather than cross-sectional comparisons. The paper also relates to Lettau, Maggiori, and Weber (2014) who show that excess returns of commodity futures sorted on the futures basis can be explained by downside risk.

The literature on "financialization of commodity markets" largely revolves around the question of whether an increase in financial speculation led to an increase in price levels or volatility, e.g. Irwin and Sanders (2011), Tang and Xiong (2012), Singleton (2014) and Hamilton and Wu (2014a), who present largely negative findings on this question. The other side of the debate is centered around the "Master's hypothesis" (Masters and White (2008)), who argue that excessive speculation in commodities drove up food and energy prices. Policy makers have at least partially taken action.[3] Irwin (2013) largely refutes this argument. We do not investigate this question in depth, but provide suggestive evidence on the matter. Figure 2 suggests that prices of "non-financialized" commodities simultaneously increased with "financialized" commodities, and it therefore seems questionable whether the price level changes can be attributed to an increase in financial speculation. In almost all of the literature on this matter, the objects of interest are outright prices or return differentials, e.g. Stoll and Whaley (2010) or Aulerich, Irwin, and Garcia (2013) rather than calendar spreads directly. One notable exception to this is Mou (2011), who examines the returns to front running the so-called Goldman roll using calendar spreads.

[3]The Wall Street Reform and Consumer Protection Act passed in 2010 aims to limit "speculative" positions in several agricultural commodities. The task of setting the precise limits and the implementation has been passed on to the CFTC, which has not yet been completed.

The Goldman roll is named after the prescribed rolling procedure of the Goldman-Sachs Commodity Index in which the index rolls, that is re-weights, twenty percent of the composition of its maturity, exchanging the closest maturities for the next closest maturities in the appropriate contracts from the fifth to ninth business days of each month. Traditionally, as detailed by Mou (2011), selling the near month of the roll and buying the following month (a trading position equivalent to a short calendar spread) ahead of this roll is an extremely predictable and profitable trading strategy. However, following 2006 large fund managers have become less susceptible to giving up ground during the roll period as can be seen directly from Figure 6.

The fact that index rolling related activity resulted in such large and predictable profits for some time leads us to believe that any study of the effects of financialization on commodity prices that ignores either the effects on calendar spreads, or the rebalancing activities as such, or both jointly may be ignoring a major part of the mechanism in which increased financialization may affect markets. Indeed many traders have been able to take advantage of this type of trading nearly as soon as these funds began trading in large quantities.[4]

Profits from index inclusion or exclusion are often explained by limits of arbitrage. Gromb and Vayanos (2010) survey several empirical and theoretical developments in this area. Our work is closely related to index investments or more generally large asset sales or purchases as in our case the degree of financialization is largely determined by index inclusion. In Vayanos and Woolley (2013), momentum arises from institutional frictions. While our setup is slightly different, the same mechanism, i.e. funds selling large quantities and thereby creating a continuation movement, also

[4] "Amber Waves of Pain," Bloomberg Businessweek, July 22, 2010.

drives our results.

Another possible aspect of the impact of financialization is pointed out by Tang and Xiong (2012), who document a strong increase in correlations between commodities and equities. This finding is important at it may help explain the returns to our strategy through common risk factors. However, we find that money managers' activities can often explain more of the returns to this strategy than traditional equity risk factors. While the evidence on whether an increased presence of investors in the commodity futures markets has led to distortions in spot prices remains inconclusive, our results indicate that the price efficiency within the maturity structure of many given commodities has changed. We find that due to constraints faced by fund managers and lack of arbitrage capital, an increase in economic agents did not always lead to an increase in information efficiency as displayed by an increase in first order autocorrelation.

3 Financialization of Commodity Markets

The term "financialization of commodities" was created in the heated policy debate following the large simultaneous price increase of various commodities between 2003 and 2008. The debate largely revolves around the question of whether speculation may have affected spot prices. There are two opposing views within this debate. The majority of academic literature, e.g. Kilian (2009), Irwin and Sanders (2012) and Fattouh, Kilian, and Mahadeva (2012) find no direct evidence of an increase in spot prices due to an increase in investment activity. They argue that the strong increase in price in many commodities between 2003 and the summer of 2008 and the subsequent price collapse is merely the outcome of an increase in demand followed by a worldwide recession and an associated decline in prices. The other side of the debate (e.g. Masters and White (2008) and many policy makers) argues that "excessive speculation" is responsible for the increase in volatility and abnormal price movements. Regardless of its impact, however, it is clear that there was an increase in financial investments in commodity markets following 2000. Barclays Capital reports that only approximately \$6 billion were invested in commodities in 2000.[5] The overall investment then grew to over \$300 billion in 2013. Figure 4 shows an estimate of assets under management in long-only commodity funds.

Insert Figure 4 here

Figure 4 not only displays a spectacular growth in assets under management (AUM) following 2004, but it also shows that AUM did not drop sharply during or following the financial crisis of 2008-09.

Contrary to investing in equity markets in which assets can be held indefinitely, investing in commodity markets usually occurs through the futures markets. Since futures contracts expire and taking physical delivery is usually costly, financial investors need to rebalance their existing positions periodically. The need to rebalance is central to the findings of this paper and we will detail this process.

In theory the rebalancing process is very simple. Suppose a fund is long the December 2014 Corn futures contract and would like to "roll into" the March 2015 Corn contract. The fund can either simply sell the December 2014 contract and buy the March 2015 contract in two separate transactions or make use of *calendar spreads*.

[5] "Dr Evil, or drivel?," The Economist, November 11th, 2010.

A calendar spread consists of the simultaneous purchase of a futures contract with one time to maturity and sale of a futures contract with a different time to maturity. For example, the Dec14-Mar15 spread consists of a long position in the December 2014 outright futures contract ("outright") and a short position in the March 2015 outright. The December 2014 contract (in general, the contract with shorter time to maturity) is usually called the "front leg" and the March 2015 contract is referred to as the "back leg". Throughout the paper, we follow the convention that having a long position in a spread consists of having a long position in the contract with shorter time to maturity (front leg) and a short position in the contract with longer time to maturity (back leg) (vice-versa for a short position).

Importantly, calendar spreads can be quoted and traded as bundles guaranteeing simultaneous execution of both legs. Most index providers mandate the existence of spreads for a commodity to be included in an index.[6] In the rebalancing example above, a fund may sell a December 2014 - March 2015 calendar spread and complete the rolling process with one transaction. The front leg of the spread will net out with the existing position, leaving the fund with a long position in the March 15 Corn futures contract. Rebalancing through calendar spreads usually entails lower overall transaction costs compared to two separate transactions in outright contracts and entails no execution risk. Given this intimate connection of calendar spreads to long-only funds' need to rebalance to rebalance their futures portfolios, it is natural to analyze calendar spreads when studying the effects of long only funds. Therefore, the objects of interest for this paper are calendar spreads. Figure 3 shows that the

[6]For example, in the S&P GSCI Manual: "...the Trading Facility on which the Contract is traded must allow market participants to execute spread transactions, through a single order entry, between the pairs of Contract Expirations included in the S&P GSCI that, at any given point in time, will be involved in the rolls to be effected in the next three Roll Periods."

fraction of open interest of noncommercial spreading has increased significantly for all the groups that are more heavily affected by financialization concurrent with the time period of rapid growth in commodity fund AUM from 2005 to 2013 but not so for the control group of "non-financialized" commodities.

Insert Figure 3 here

At this point, the rebalancing process may seem like an innocuous and rather technical task. However, depending on the shape of the term structure, it can be quite costly. For example, the United States Natural Gas Fund (UNG), which invests primarily in the front month (Henry Hub) natural gas futures contract, lost more than 90% in value between January 2008 and December 2013, while the spot price of natural gas only declined by 45%. Given this discrepancy in returns, efficient management of the roll process is a critical task. More generally, the process of providing exposure to commodity returns in an efficient, roll-cost-conscious manner can be challenging and may involve large gains or losses and is therefore a priority for many money managers. If the term structure is upward sloping (contango) rolling is costly as the contract to be rolled into is more expensive than the contract to be rolled from. Similarly if the term structure is downward sloping (backwardation), rolling results in positive returns.

Except for funds that mechanically track one of the broader commodity indices, little is known about funds' exact investment behavior. A recent article in the Wall Street Journal describes the behavior of the three largest funds in the field, namely the SPDR Gold Trust, which largely invests in physical gold bullion thereby eliminating the rebalancing problem; the Pimco Commodity Real Return Strategy Fund, which is benchmarked against the Dow Jones UBS Commodity Index but leaves the manager some leeway in the choice of commodities and maturities; and the largest ETF, the DB Commodity Index Tracking Fund ETF, which selects contracts to "limit the damages from contango or maximize the benefits from backwardation".[7]

4 Commodity Futures Markets

4.1 The Trading Strategy

Let $F_{n,t}$ denote the price of an n-period futures contract at time t.[8] For every t and within each commodity market, there are several futures contracts traded that differ by their time to maturity n. In order to describe the strategy we employ, we will concern ourselves with three different futures contracts (for each commodity) denoted by $F_{n_1,t}$, $F_{n_2,t}$ and $F_{n_3,t}$, where $n_1 < n_2 < n_3$. $F_{n_1,t}$ denotes the contract closest to delivery (the "nearby" or front-month contract), $F_{n_2,t}$ denotes the contract next to delivery after the nearby contract (often called the "next-out" contract), and $F_{n_3,t}$ denotes the contract up for delivery approximately one year from time t. In general the strategy trades in *calendar spreads*.

First, we consider the spread between the nearby contract and the next out contract. We call this spread the signal spread, i.e. $S_t^{\text{signal}} := F_{n_1,t} - F_{n_2,t}$. In addition to the signal spread, we will consider the spread between the nearby contract and the contract up for delivery approximately one year from time t. We call this spread the

[7] Commodities: To Buy or Not to Buy, Wall Street Journal, April 26th, 2014.

[8] To keep the notation simple, we will not introduce different symbols for different commodity markets in this section.

trading spread, i.e. $S_t^{\text{Trading}} := F_{n_1,t} - F_{n_3,t}$, or sometimes just the year spread. As the name indicates, we generate signals for buying and selling (the trading spread) by analyzing the signal spread. More precisely, we monitor the 50-day moving average of $s_t^{\text{Signal}} := \ln F_{n_1,t} - \ln F_{n_2,t}$ and generate a long signal if the current difference (in logs) is greater than the 50-day moving average and a short signal if the current difference in logs is smaller than the 50-day moving average, i.e.

$$\text{Signal}_t = \begin{cases} \textbf{long} & \text{if} \quad \ln F_{n_1,t} - \ln F_{n_2,t} \geq \frac{1}{50}\sum_{i=0}^{49} \ln F_{n_1,t-i} - \ln F_{n_2,t-i} \\ \textbf{short} & \text{if} \quad \ln S_{n_1,t} - \ln S_{n_2,t} < \frac{1}{50}\sum_{i=0}^{49} \ln F_{n_1,t-i} - \ln F_{n_2,t-i}. \end{cases}$$

As for any strategy that aims to be implementable in real time, there needs to be a temporal gap between signal generation and taking of positions, we there wait one entire trading day to enter a position based on the above signals. For concreteness we assume that the entry price for each new signal is the next day's settlement price. We can therefore summarize the position on each day using the notation as

$$\text{Position}_t = \begin{cases} F_{n_1,t} - F_{n_3,t} & \text{if} \quad s_{t-1}^s \geq \frac{1}{50}\sum_{i=0}^{49} s_{t-1-i}^s \\ -(F_{n_1,t} - F_{n_3,t}) & \text{if} \quad s_{t-1}^s < \frac{1}{50}\sum_{i=0}^{49} s_{t-1-i}^s. \end{cases}$$

Figure 1 illustrates the trading process.

Insert Figure 1 here.

The difference between the nearby and the next-out contract (the signal spread) has a natural interpretation and connection to carry, the difference between the spot and the futures price. The futures prices is given by

$$F_t = P_t(1 + r_{ft} - \delta_t), \tag{1}$$

where P_t is the spot price, r_{ft} is the risk free rate, and δ_t is often interpreted as the convenience yield net of storage cost. Since neither storage cost nor the convenience yield are directly observable, however, δ_t is merely a parameter chosen so that the equation holds. The (normalized) difference between the spot and the futures prices (referred to as the basis or carry) can then be expressed as

$$C_t = \frac{P_t - F_t}{F_t} = (\delta_t - r_{ft}) \frac{1}{1 + r_{ft} - \delta_t}. \tag{2}$$

Fama and French (1987) document that carry is often a good predictor of spot prices and Koijen, Moskowitz, Pedersen, and Vrugt (2013) apply this concept to other asset classes. However, in most commodity markets, in particular for agricultural products, the spot market is very disaggregated, which renders the spot price almost unobservable. Therefore, one usually proxies for the spot price with the nearby futures contract ($F_{n_1,t}$) and uses the next-out futures contract ($F_{n_2,t}$) as the futures contract in (2). One can therefore re-write the expression for carry as

$$C_t = \frac{F_{n_1,t} - F_{n_2,t}}{F_{n_2,t}(n_2 - n_1)}. \tag{3}$$

Given (3), the construction of our strategy is rather intuitive. However, it is important to stress that we are not interested in cross-sectional differences in carry or in using carry to predict future spot prices. We have two important differences from these exercises. First, the absolute level of C_t or even its sign is irrelevant for the strategy, and second, we are not interested in predicting future spot prices but rather in predicting the future spread between the nearby and the year contract, S^{n_1,n_2}. Therefore, the strategy can be interpreted as "momentum in carry" or "momentum in the basis". We choose this naming as we are buying an asset (here a calendar spread) whose carry has increased or selling one whose carry has decreased. However, as noted before the absolute level is not important; indeed we often buy negative carry assets.

In the literature, it is common to use carry as a predictor of future spot prices directly. Fama and French (1987) document that carry can predict future spot prices. In particular, high carry indicates increasing prices and low carry indicates falling prices. This relationship does not necessarily hold in our trading strategy, nor should it be expected to as we are dealing in calendar spreads, which are the first difference of the futures curve. We are more concerned with relative changes (relative to a moving average) in the nature or degree of contango or backwardation than we are with its absolute level. In essence we aim to profit from steepening and flattening of the futures curve.

We take positions in year spreads relative to the nearby—next-out spread for two reasons. First, we expect to see effects at many places along the term structure as funds are actively managing their roll yield risk along the term structure. By analyzing year spreads, we can be somewhat agnostic about pinpointing which contracts are affected by rebalacing activities. Since a year spread can be written as the sum of all one-contract spreads, e.g. $F_{n_1,t} - F_{n_{12},t} = (F_{n_1,t} - F_{n_2,t}) + (F_{n_2,t} - F_{n_r,t}) + ... + (F_{n_{11},t} - F_{n_{12},t})$.

Using year spreads has the above mentioned advantages for all commodities except for meats. Meats have the peculiarity that the contract is cleared in weight of a certain USDA quality, but the delivery is in live animals. The concept of carry is therefore hard to apply because the animals can be affected by a number of external factors, such as diseases, shelter availability, and various other uncertainties. In practice this means that actually carrying forward cattle is prohibitively costly. We see this in the futures prices, in which the correlation between the year contract and the nearby contract is considerably lower for meats than for all other groups. We therefore, expect qualitatively different results for meats.

In theory entering into a futures contract can be done at zero initial cost, yet in practice it requires setting up a margin account. For example, as of this writing to trade \$102,770 worth of crude oil futures one need only to post \$3,190 in initial margin and keep a minimum of \$2,900 thereafter in maintenance margin.[9] The margin requirement for calendar spreads is typically an order of magnitude less than for outright futures contracts because spreads are not exposed to "level risk" due to their hedged nature arising from having offsetting positions in fairly highly correlated assets. In addition to the large amount of leverage that is typically afforded to futures margin accounts, spread prices can frequently be negative or even equal to zero. We must therefore make assumptions when calculating returns to trading spreads. We follow Moskowitz, Ooi, and Pedersen (2012) and make the following assumptions about collateral in order to compute returns. If we are buying a futures contract, we assume that we are putting up the full collateral and thus compute returns on long positions as $R_t = \frac{F_{t+1}-F_t}{F_t}$ and similarly for short positions as $R_t = -\frac{F_{t+1}-F_t}{F_t}$. Therefore for our purposes the returns on calendar spreads are merely the sum of the returns on the long and the short legs of the spread position. This means that our reported results are *extremely* conservative because they are not leveraged at all in a trading environment that generally operates with large amounts of leverage.

[9] Current margin requirements for crude oil can be found on the CME website, `http://www.cmegroup.com/trading/energy/crude-oil/light-sweet-crude_performance_bonds.html`.

4.2 Data

Our data come from daily settlement prices for 25 listed commodities on various exchanges owned by the Chicago Mercantile Exchange Group (CME) and the Intercontinental Exchange (ICE). We use the 18 commodities listed in Table 1 as a treatment group as they are contained in most indices.[10] Rough rice (RR), oats (O), soybean oil (BO), random length lumber (LB), frozen orange juice (OJ), platinum (PL) and palladium (PA) serve as a control group as they are not contained in the largest indices, namely the Bloomberg Commodity Index and the SP-GSCI. Note that we cannot speak of a control group in the sense of a randomized experiment here as the selection into an index is not random and usually based on world production and liquidity. However, this selection process will not be problematic to the interpretation of results as it is likely to bias the effects downward. Settlement prices for the front month represent the volume weighted average price (VWAP) over a predetermined time interval near the end of the trading session for each market. This time interval is different for each market or sometimes market sector, and settlement prices for later months are usually determined from analyzing the prices of the bundle-traded calendar spreads between listed months. The specific rules for determining the daily settlement prices for each market can be found on the relevant exchanges' websites.[11] We now address several other relevant futures-specific trading details.

[10] For the heating oil contract only, the physical underlying commodity was changed beginning with the May 2013 contract. The contract specifications relating to delivery and quantity of the underlying commodity remain the same, however. This fact, along with the fact that the listed heating oil contract with New York Mercantile Exchange (NYMEX) trading symbol HO has continued to be included in commodity indices and tracked by commodity funds means that our results for the months following this change should be consistent with the months preceding it.

[11] For example, for energy contracts on the CME-owned NYMEX, the following document contains the rule for determining settlement prices: http://www.cmegroup.com/trading/energy/files/NYMEX_Energy_Futures_Daily_Settlement_Procedure.pdf.

Each market for futures on a given commodity consists of many different futures contracts with different maturities spaced throughout each year in a repeating pattern (listing cycle), although each market can have a different set of maturities (listed months) per year. Corn, for example, has listed months for delivery of the underlying Corn in March, May, July, September, and December of each year, while Crude Oil has listed months in every month of the year.

In order to compute returns to our strategy continuously, we need to set convention on when we roll contracts. We always want to be only trading the year spread whose front leg is the front month, which is the month that has not rolled and is nearest to expiration. As in Szymanowska, De Roon, Nijman, and van den Goorbergh (2014), prices from the month prior and during the delivery month are excluded from trading to avoid sometimes highly irregular price movements as futures contracts near delivery. Formally, we say a contract has rolled if we are on or past the first business day of the calendar month that precedes the contract's nominal delivery month. If we are trading corn, for example, from the period of February 1 to March 31 we would be trading the May contract (as the front leg of the spread) since the March contract rolls into May on February 1 and since the May contract rolls into July on April 1.

Note that we look at the moving averages of (logs of) all available one-contract calendar spreads simultaneously on any given date and keep track of their signals even when we are not trading them. Thus we know what the signal will be at the time when we must roll into each contract because we have been comparing every spread's (log) price to its own moving average even during time periods when those contracts were not the front months. As another example trading corn, suppose the date is March 25 so that the front month is May. The next month would be July, which we would have to start trading on April 1. We already know our moving averages and prices for the July contract, and when April 1 comes along, we close any position we have in the May contract according to our trading rules (explained in section 4.1, and immediately open a new position in the July contract according to what the signal for July says for that day, completely independent of what the signal for the May contract would have been. Hence there is no confusion of information across maturities and signals because all trading is done on a contract-by-contract basis, and our rolling rule merely tells us which contract we are actively trading at any given time. In addition, since we have a delay of one day between our signal generation and our trading activity, the roll from the above example would more specifically go like this. The last signal for the May contract would occur on March 31 and on April 1 we would close our May corn position. The first signal for the July contract would occur on April 1, and on April 2 we would open our July corn position. So there is only ever one trade per day in any contract.

5 Empirical Results

5.1 Return Analysis

In our baseline results, we report daily and monthly returns for the groups of commodities (we apply an equal weighting withing groups) and an equal weighted portfolio for the contracts listed in Table 1. Table 2 presents summary statistics for the returns over several subsamples.

Insert Table 2

From Table 2 we can see that both raw returns and Sharpe ratios are significantly greater in the period from 2005 to 2013 relative to the period from 1990 to 2004.[12] This becomes even more evident if we look at a chart of the cumulative returns (Figure 2).

Insert Figure 2

From the lower panel of Figure 2 we can see that commodities as an asset class earned high return between 2003 and mid 2008 (an equally weighted portfolio of the 18 commodities considered here would have yielded a average return of 16% annualized). However, the returns to our strategy did not decline strongly in the second part of 2008 as the broad commodities asset class did. Moreover, we can see that the outright prices of the commodities in the control group also increased strongly, but the returns to trading the strategy in the control did not. We provide an answer for what could account for this discrepancy later in the paper when we discuss the effects of financialization on commodity term structures in greater detail.

5.1.1 Risk-Adjusted Returns

Since it is possible that the high returns to our strategy are merely compensation for risk, we first consider risk-adjusted returns by employing a large number of factors to attempt to explain them. To assess potential abnormal returns, we estimate (for the groups of commodities and the equally weighted portfolio) regressions of the following form

[12] As a comparison, the CRSP value-weighted stock index had an annualized return of 10.3% and an annualized standard deviation of 15.4% between 1990 and 2013; between 1990 and 2004 the annualized return was 11.5% with a volatility of 14.9%; and between 2005 and 2013 the annualized return and volatility were 8.5% and 16%, respectively.

$$R_t = \alpha + \sum_{i=1}^{k} \beta_i f_{i,t} + \varepsilon_t, \tag{4}$$

where $f_{i,t}$ denotes the return of the i-th factor at time t. In Table 3 we first try to explain the portfolio returns with the most common risk factors for equities (i.e. the Fama and French (1992) factors, the momentum factor of Jegadeesh and Titman (1993) and the liquidity factor of Pastor and Stambaugh (2003)) then we also include the time series momentum factor for commodities and the value factor for commodities of Moskowitz, Ooi, and Pedersen (2012). Most factors employed in Table 3 are not significant and the overall explanatory power of these factors for the monthly returns of this strategy is very low.

On a portfolio level we see a positive and significant alpha for the second subperiod and also for the full sample period. Tables 19, 20, 21, 22 and 23 show the analogous results for the commodity groups. Except for meats, as we expected, the results are qualitatively very similar.[13] The explanatory power of these factors is in general very low.

One might argue that the results for the "classical" equity factors in Tables 3, 19, 20, 21, 22 and 23 are indeed no surprise as these factors were employed mainly in the equity markets and with the exception of the value, momentum, and time series momentum factor of Moskowitz, Ooi, and Pedersen (2012), there is per se no reason why these factors should explain the returns generated by this strategy. We therefore explore several alternative factors, namely VIX and realized volatility to capture a

[13]As shown in Table 1, *Energy* contains Crude Oil, Natural Gas, Heating Oil and Gasoline, *Grains* contains Corn, Wheat, Soybeans, and Soybean Meal, *Softs* contains Cocoa, Cotton, Coffee and Sugar, *Meats* contains Live Hogs, Feeder Cattle, and Live Cattle and *Metals* contains Copper, Silver, and Gold.

possible variance risk premium, the hedge fund factors of Fung and Hsieh (2001)[14]. The hedge fund factors are trend following factors and therefore natural to explore, but they also give us an indication as to what extent hedge funds are following the same strategy. In addition, we use the commodity factors of Szymanowska, De Roon, Nijman, and van den Goorbergh (2014).[15] Table 4 shows the results if we employ these factors on the equal weighted portfolio of commodity returns generated by our strategy and Tables 24, 25, 26, 27 and 28 show the analogous results for the commodity groups.

In summary, the abnormal performance of this trading strategy cannot be explained by common risk factors, and therefore the returns are not a result of high exposure to known sources of systematic risk.

5.1.2 Downside Risk

In Section 4.1 we call this strategy a “momentum in carry” approach. The carry trade in the currency markets is investigated in great detail in Eichenbaum, Burnside, and Rebelo (2007) and the concept of carry is applied more generally to other asset classes in Koijen, Moskowitz, Pedersen, and Vrugt (2013). Burnside, Eichenbaum, Kleshchelski, and Rebelo (2011) argue that the carry trade in currency is subject to downside risk or more generally largely a compensation for downside risk. A natural question to ask is whether our returns to momentum in carry can be similarly explained. To address the compensation for downside risk, we follow an approach similar to Lettau, Maggiori, and Weber (2014) and re-write equation (4) in terms of

[14] The factors can be downloaded from `http://faculty.fuqua.duke.edu/~dah7/DataLibrary/TF-FAC.xls`.

[15] Contrary to the other factors, these factors are not available on the authors' webpages. We therefore constructed these factors ourselves using our commodity data set.

downside and upside factors, i.e.

$$R_t = \alpha + \sum_{i=1}^{k} \beta_i^+ f_{i,t}^+ + \sum_{i=1}^{k} \beta_i^- f_{i,t}^- + \varepsilon_t, \tag{5}$$

where $f_{it}^+ = \begin{cases} f_{i,t} & \text{if} \quad f_{i,t} \geq \bar{f}_{i|t} - \sigma_{i|t} \\ 0 & \text{if} \quad f_{i,t} < \bar{f}_{i|t} - \sigma_{i|t} \end{cases}$, where $\bar{f}_{i|t}$ denotes the time-t conditional mean of the factor return for factor i at time t and $\sigma_{i|t}$ denoets the time-t conditional standard deviation of the factor return, ($f_{i,t}^-$ is defined analogously). If $\beta_i^- > \beta_i^+$ we can infer that the returns have more downside exposure to factor i. From Tables (in Appendix C) 29, 30, 31 and 32 we can see that there is no strong evidence for downside risk exposure.

5.1.3 Active-Passive Return Decomposition

The analysis of Section 5.1.1 shows that the returns cannot be explained by known sources of systematic risk. As the true sources of systematic risk are not known, these models might be misspecified and display positive alphas merely as a results of misspecification. We could therefore incorrectly conclude that the strategy delivers positive abnormal returns, where the contribution from actively trading the strategy is actually zero. To address this concern, we decompose the return into an active and passive component, where the active component can be interpreted as timing skill.

Lo and MacKinlay (1990) and Lo (2008) present a decomposition of returns into an active component and a risk premium component. Let $w_{i,t}$ denote the position we are holding (i.e. whether we are long or short) and let $R_{i,t}^{yr}$ denote the return on a year spread. We can write the expected returns on trading calendar spreads for the groups of commodities as

$$E[R_{pt}] = \sum_{i=1}^{n} E[w_{i,t} R_{it}^{yr}] = \underbrace{\sum_{i=1}^{n} cov\left(w_{i,t}, R_{it}^{yr}\right)}_{\text{active component}} + \underbrace{\sum_{i=1}^{n} E[w_{i,t}] E[R_{i,t}^{yr}]}_{\text{passive component}}. \tag{6}$$

This decomposition deserves some explanation. Typically, portfolio weights are not considered random variables, but here they are treated as such. The reason for this treatment is the following. The weights are the outcome of estimation and thus a function of returns (i.e. random variables) and are therefore suitably treated as random variables. From (6) we can define the active ratio (AR), i.e. the fraction of the return that can be attributed to active management.

$$\% \text{ Active} = 100 \times \frac{\sum_{i=1}^{n} cov\left(w_{i,t}, R_{i,t}^{yr}\right)}{\sum_{i=1}^{n} cov\left(w_{i,t}, R_{i,t}^{yr}\right) + \sum_{i=1}^{n} E[w_{i,t}] E[R_{i,t}^{yr}]}. \tag{7}$$

If the portfolio weights were completely random or constant as for a buy-and-hold strategy, they would be uncorrelated with the returns and hence the active ratio, % Active, would be zero. Table 5 shows the active ratio for the 5 commodity groups and the control group.

Insert Table 5 here

From Table 5 we can see that we have a significant active contribution for the 5 financialized groups and no significant active contribution for the control group. This suggests there may indeed be a mechanism that our trading strategy can detect in financialized markets only. The returns to the strategy are the result of active timing decisions and are indeed abnormal.

5.1.4 Return Breakdown

The results so far show that we earn significant abnormal returns on a portfolio of commodities and on most commodity groups in the second part of the sample. To understand the results better, Table 6 further breaks down the returns and shows returns from long and short positions (in spreads) and also from long and short positions of the individual legs of the spreads.

Insert Table 6 here

There is no clear pattern in terms of long versus short returns as their contribution to the total return is roughly equal. Table 6 shows that the return contribution (to the total return) is larger by the front leg than by the back leg of the spread. This suggests that the back leg (of the year spread) largely serves as a hedge and helps to reduce risk. Table 7 shows the volatility from trading spreads and the volatility of the front leg and back leg separately, i.e. if we had only taken a one-sided position. We can see that trading spreads helps to reduce volatility by a large amount.

Insert Table 7 here

5.2 Financialization as a Potential Mechanism

In section 5.1 we document that the returns are abnormal in the sense that they are not explained by traditional risk factors. Moreover, we also document a sharp increase in returns around 2005, which corresponds to the beginning of the rapid growth in assets under management in funds that invest in commodity markets (see Figure 4). Therefore it is natural to surmise that the growth in the assets of these funds may have had an effect on the returns to our strategy. But there is additional significance to analyzing possible effects of commodity funds' investing practices on calendar spreads. To our knowledge, as discussed in the literature review, no paper has analyzed the effect of commodity fund investment growth on the term structure of commodities separately from the returns to individual futures contracts or spot prices. The papers who have analyzed these effects generally report negative findings of any substantial impact on prices directly. However, since calendar spreads arise so naturally in funds rebalancing activities, any analysis of the effect of commodity funds on the markets that ignores the effects on the term structure is potentially incomplete. In this sense, analyzing the returns to our term structure based trading strategy vis-a-vis the effect of commodity fund investing is a logical endeavor that fills a void in existing research.

5.2.1 Temporal Dependence

Since the nature of the strategy is trend following, it is natural to analyze the autocorrelation of calendar spreads in the time period in which we saw low investments in commodities and the time period from 2005 onward when such investment levels grew rapidly. We first test for an increase in first order autocorrelation in the second part of the sample for the front leg and back leg of the spread separately. Table 8 shows the autocorrelation of the front leg return, which only changed significantly for energy. Table 9 show that the autocorrelation in the back leg return decreased significantly for grains and increased significantly for energy and metals. However, Table 10 shows that the autocorrelation in year spreads increased significantly for grains, softs and the control group. Adding the pre 2005 and post 2005 effects, we can see that the autocorrelation is positive and significant for grains, softs, energy and metals. From a purely technical point of view, we therefore expect a trend following strategy to generate positive returns.

We aim to link the increase in autocorrelation to the money managers net long positions from the CFTC Committment of Traders (COT) report, which is available from

2006 onward. Table 11 shows the regression results of the following specification for each group.[16]

$$R_{i,t}^{yr} = \alpha + \beta_1 R_{i,t-1}^{yr} + \beta_2 \text{Money Managers}_{i,t-1} + \beta_3 R_{i,t-1}^{yr} \times \text{Money Managers}_{i,t-1} + \varepsilon_{i,t},$$

where Money $\text{Managers}_{i,t-1}$ denotes the net long fraction of total open interest across all contracts money managers are holding at time $t-1$. Table 12 shows the counterfactual autocorrelation estimated over the same time period.

Insert Tables 11, 12 here

From Table 11 we see that for grains and softs, the first order autocorrelation is no longer significant after controlling for fund managers positions, and the interaction term is positive and significant. For energy and metals, we also have a positive and significant interaction term, but the first order coefficient is still positive and significant. For meats and the control group, we see no significant effect, i.e. their autocorrelation cannot be explained by money managers positions.

We next explore whether fund managers' positions exhibit predictive ability for future returns to our strategy. For each group we estimate the following model.

$$R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_2 \Delta OI_{i,t-1} + \beta_3 \text{Money Managers}_{i,t-1} + \varepsilon_{i,t}$$

Insert Table 13 here

[16]The specification can best be understood in the following way. Consider first the simple model, $R_t^{yr} = \alpha + \beta_1 R_{t-1}^{yr} + \varepsilon_t$. Then we make the following substitution, $\beta_{1,t-1} = \gamma_0 + \gamma_1 \text{Money Managers}_{t-1}$. This is effectively making the coefficient of first order autocorrelation a function of the money managers' positions.

From Table 13 we can see that there is evidence of predictability for grains, softs and metals. For the other groups, including the control group, we do not find significant predictability of the strategies return using the money managers positions.

The predictive results appear relatively weak at first sight. We need to put the results in context of the data limitations given through the public availability of positions reports, i. e. the CFTC COT data in this particular analysis. First, our returns are generated by daily timing decisions for calendar spreads, but the CFTC only publishes this report *weekly*. Our trading decisions are therefore unlikely to overlap with the report data. Second, the data do not indicate the specific contracts in which money managers take positions. Third, and perhaps most significant is the fact that the CFTC data are published each Friday but represents data gathered on each preceding Tuesday. Our weekly return analysis only focuses on the Friday based week and therefore does not line up with the data we are attempting to use as explanatory. This could pose a problem because it is possible for the concurrent money manager positions to have an effect on our positions during a period of smaller frequency than we are able to capture. Furthermore, since we are always using essentially "old data" in our estimation, we are also tacitly making the assumption that nothing important happens in the market between the collection and publication of the data. Given these severe limitations, it is quite surprising that we find evidence of predictive ability to the returns to our strategy using the public CFTC data. However, the small indications of financialization's impact on our novel term structure momentum strategy lead us to believe that there are effects that we can estimate given more suitable data. This is certainly an area warranting more future research.

5.2.2 Cross Sectional Results

In Section 3 we outlined the rebalancing process of long only funds and the crucial role of calendar spreads in this process. It is therefore natural to suppose that the amount of noncommercial spreading can serve as a proxy for the "degree of financialization". Spread accounting is crucial for this observation. Funds sell spreads to rebalance their positions, but because they are already long the front leg of the spread, this nets out and they are left with a long position in the back leg thus completing the equivalent of an outright contract roll. Therefore, their activities will not appear as spreading in the CFTC COT data. What appears as spreading in the data is the counterparties' positions. Recall Figure 3, which illustrates the percentage of open interest in noncommerical spreading. In order to test if noncommercial spreading can explain the variation in returns we estimate the following pooled model for quarterly returns. We use the slope of the term structure, inflation, GDP growth, outright return and the VIX as control. We use inflation and gdp growth as control variables as they are found to be correlated with commodity returns, e.g. Gorton and Rouwenhorst (2006). VIX is often used as a measure of market fear, we control for it as intermediation capital may be scarce in times of high VIX, which may affect the returns to this strategy.

$$\begin{aligned} R_{i,t} &= \alpha + \beta_1 \text{Abnormal Spreading}_{i,t} + \beta_2 \text{Slope}_{i,t} + \beta_3 \text{Inflation}_t \\ &\quad + \beta_4 \text{GDP Growth}_t + \text{VIX}_t + \varepsilon_{i,t} \end{aligned} \tag{8}$$

Insert Table 14 here

We define abnormal spreading in (8) as the difference between the average level of spreading in a quarter and the average level of spreading from 1990 to 2000.[17] Slope is defined as the average of $\ln F_{n_2,it} - \ln F_{n_1,it}$ for a given quarter. In columns one and two of Table 14, we estimate this specification across both the treated and control commodities, whereas in column three and four, we show results only for the treated commodities. In columns two and four, we included time fixed effects. We can see that abnormal spreading is strongly significant in all specifications. We therefore conclude that this measure of the degree of financialization explains part of the cross-sectional differences in returns to this strategy.

5.2.3 The Term Structure of Open Interest and Volatility

Given the results of Section 5.2.1, it is possible to suspect that there may have been a shift in term structure activities that has driven the results. In the following, we document that there is indeed more activity in the long end of the term structure, but it happens equally for the treatment and the control group. It is therefore unlikely that the returns to our strategy for the financialized commodities can be explained only by a change in activity along the term structure.

Futures contracts traditionally exhibit a very strong concentration of open interest in the nearby contract.[18] If fund managers are indeed actively managing their term structure (rollover risk) we expect that they will do so with some notion of optimality in mind. If the term structure is upward sloping (contango), it is costly to roll. If it is in addition concave, it might be relatively cheaper to roll into a later contract

[17] We have also used the level of spreading without any adjustment, the results are not affected qualitatively by this change.

[18] Of the commodities eexamined, the 25-th percentile of open interest in the nearby contract (on any given day prior to the roll) was 38%, the median was 50% and the 75-th percentile was 64% in the pre 2005 period.

rather than the next contract. Therefore for commodities for which the term structure is in contango, we expect to see relatively more open interest in contracts with longer maturities compared to the pre-financialization period. If the term structure is downward sloping (i.e. in backwardation), then it is in fact cheaper to buy a longer dated futures contract and there is little need to manage term structure risk. In the case of backwardation, fund managers may decide to maximize (positive) gains from rolling, but they have to keep liquidity in mind as longer dated contracts are usually less liquid than the nearby contract.

It is also clear that the term structure is not constant over time. The term structure of a particular commodity may be upward sloping at times and downward sloping at other times. However, we aim to examine whether it is on average upward or downward sloping. As prices are typically non-stationary, we normalize the prices (within one commodity) every day by the price of the nearby contract. We then estimate the following model:

$$100 \times \frac{F_{n_i,t}}{F_{n_1,t}} = \beta_0 + \beta_1 n_i + \beta_2 n_i^2 + \text{Delivery Month Dummies} + \varepsilon_t. \tag{9}$$

The delivery month dummies are necessary to control for the effects of seasonality, for example the heating season in natural gas or heating oil, or the crop cycle in grains. If $\beta_1 > 0$ and $\beta_2 < 0$ the term structure is (on average) upward sloping and concave. Table 16 shows the estimates for commodity groups in our sample.

Insert Table 16, 15 and 17

From Table 16, we see that on average the groups grains, softs and energy and the control group were in contango. The coefficient for metals and meats is positive, but insignificant. Grains, softs and energy were on average significantly in concave contango. However, the adjusted R^2 is relatively low for most groups which indicates that the slope of the term structure may have changed often.

From Tables 15 and 17 we see that both volatility and open interest increase at the longer end of the term structure. However, this is equally the case for the more financialized groups and the control group. It is therefore unlikely that the increase in returns to our strategy in the second part of the sample can merely be explained by the shape of the term structure.

6 Conclusion

In this paper we show that a simple momentum-type strategy in commodity calendar spreads generates abnormally high returns that are characterized by two important features. First, they are not related to variation in risk, and second, they exhibit a marked increase that corresponds to the growth in long-only investments in commodities, i.e. financialization of commodities.

Long-only mutual funds in commodity markets automatically have to be "more active" than their equity counterparts. Whereas the latter can merely buy and hold infinitely lived securities, the former have to roll their positions periodically as futures get closer to expiry. The shape of the term structure determines the cost of rolling. For many commodity markets, rolling has traditionally been rather costly. Therefore, we expect that mutual funds will actively manage their term structure risk while at the same time not detailing how they do so to avoid becoming subject to front running. However, while commodity mutual funds may get more and more sophisticated in managing their term structure risk, they can never avoid the risk completely. We therefore expect that some of these effects documented will not vanish as long as mutual funds are such a large part of the market and arbitrage remains scarce.

In fact, the funds' rebalancing demand shocks introduce a limit of arbitrage for speculative traders who take positions in calendar spreads along the forward curve and whose deployment of risk capital may be slow moving, allowing temporary pricing inefficiencies to persist for some time. Many other papers that have examined the effects of the financialization of commodities have focused on spot prices, or outright futures contract prices and have had little success in finding significant effects of large commodity funds' trading activity on these prices. However, by focusing on calendar spreads, the natural trading vehicle of any long term commodity trader, especially buy-and-hold type mutual funds, we show that funds' trading activities do indeed affect commodity spread returns.

Future research should explore the mechanism documented here in a plausible economic framework in which fund managers' behavior is explicitly modeled. Moreover, while the success of carry for future returns (at least cross-sectionally) has been documented in the literature, our strategy does not rely on the absolute level of carry but rather on changes in carry. It is therefore a "time series momentum in carry" strategy which could be explored in other asset classes.

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A Figures

Figure 1: The Trading Process

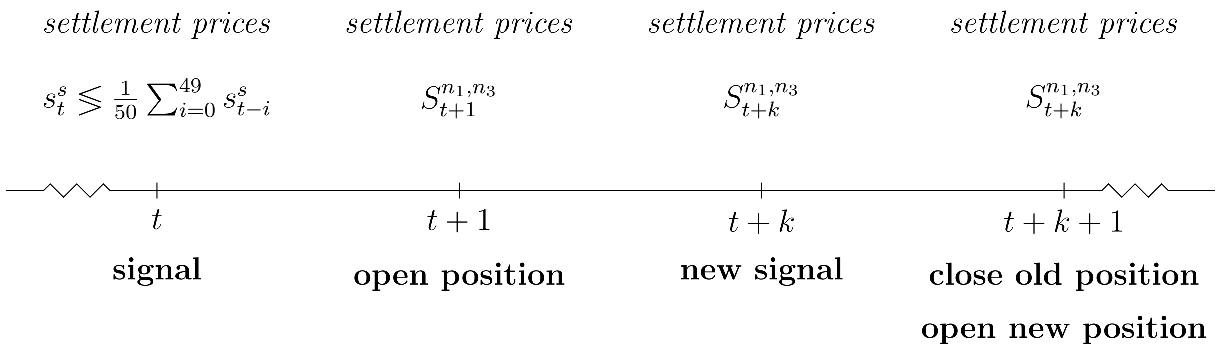


Figure 2: Cumulative Return from the Strategy vs. a Buy-and-Hold Strategy

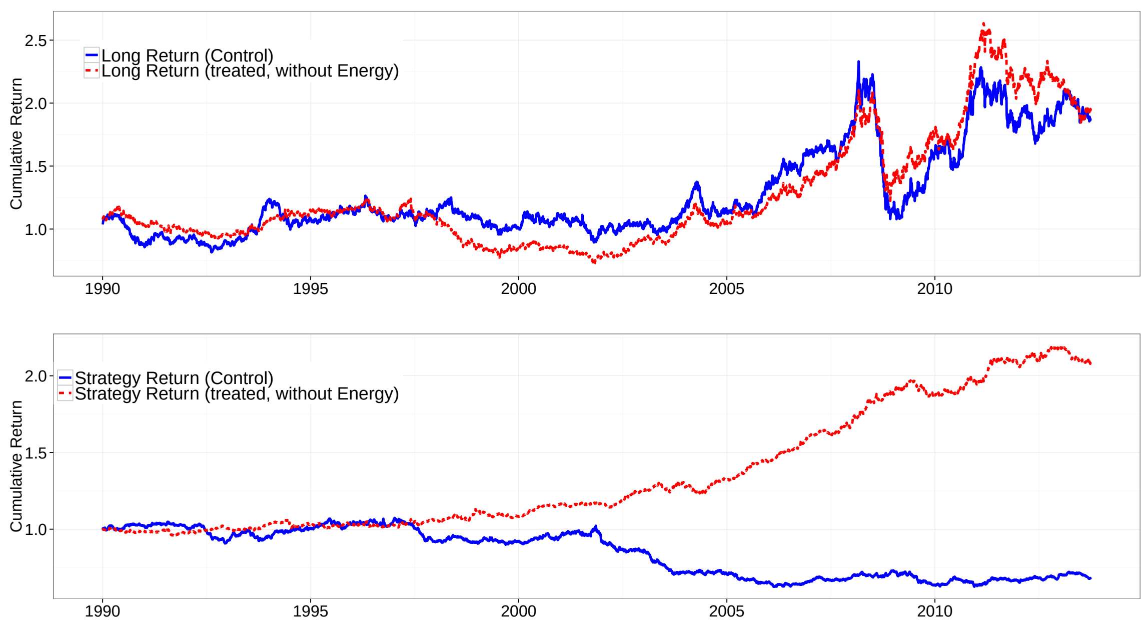


Figure 3: Noncommercial Spreading as a Fraction of Total Open Interest

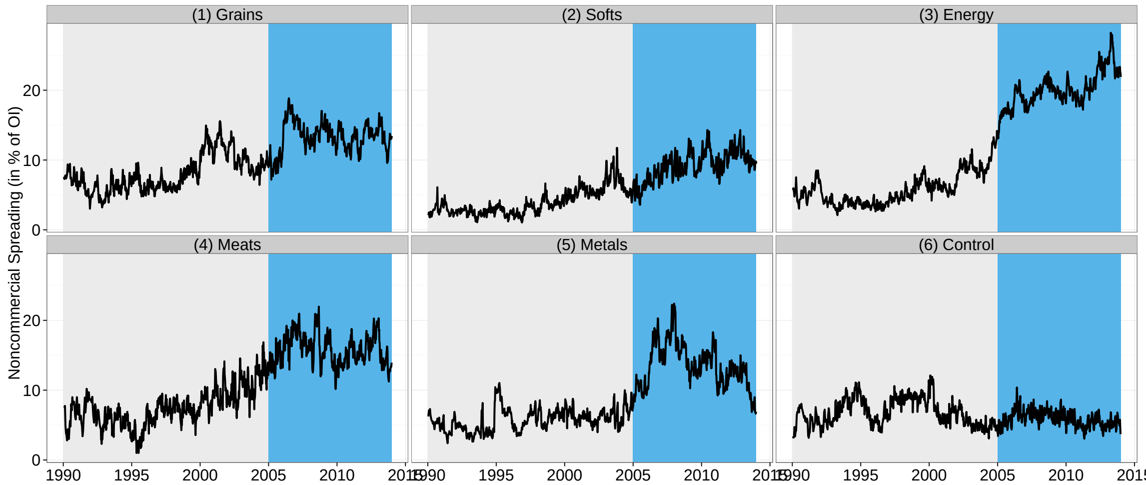


Figure 4: Commodity Assets under Management

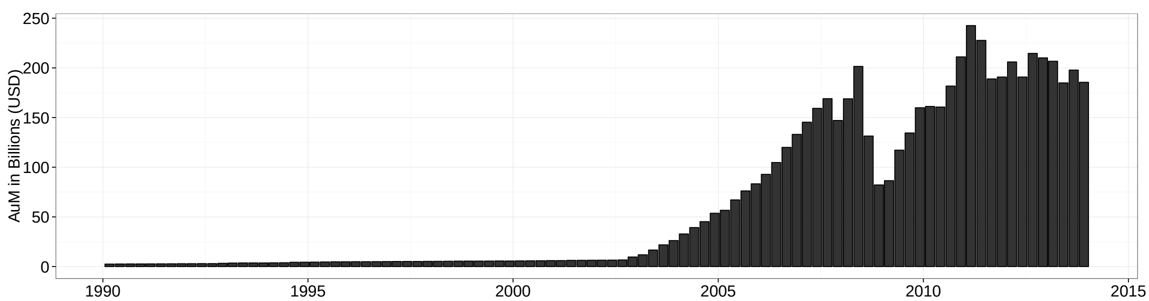


Figure 5: Timeline for the Mechanical Strategy

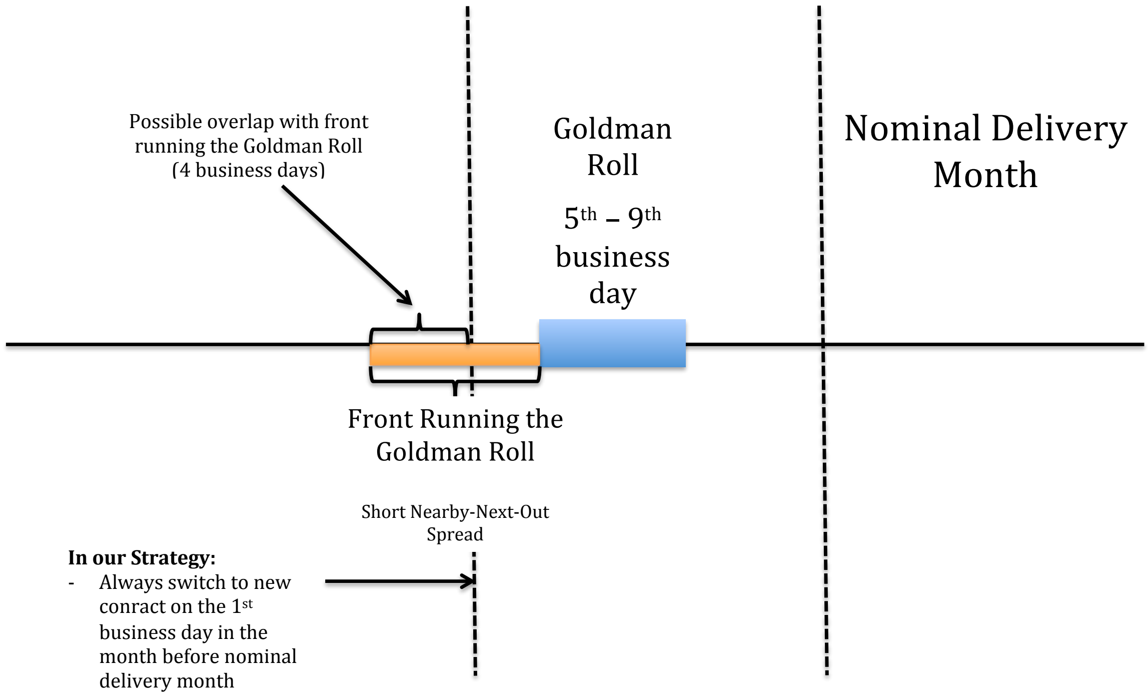
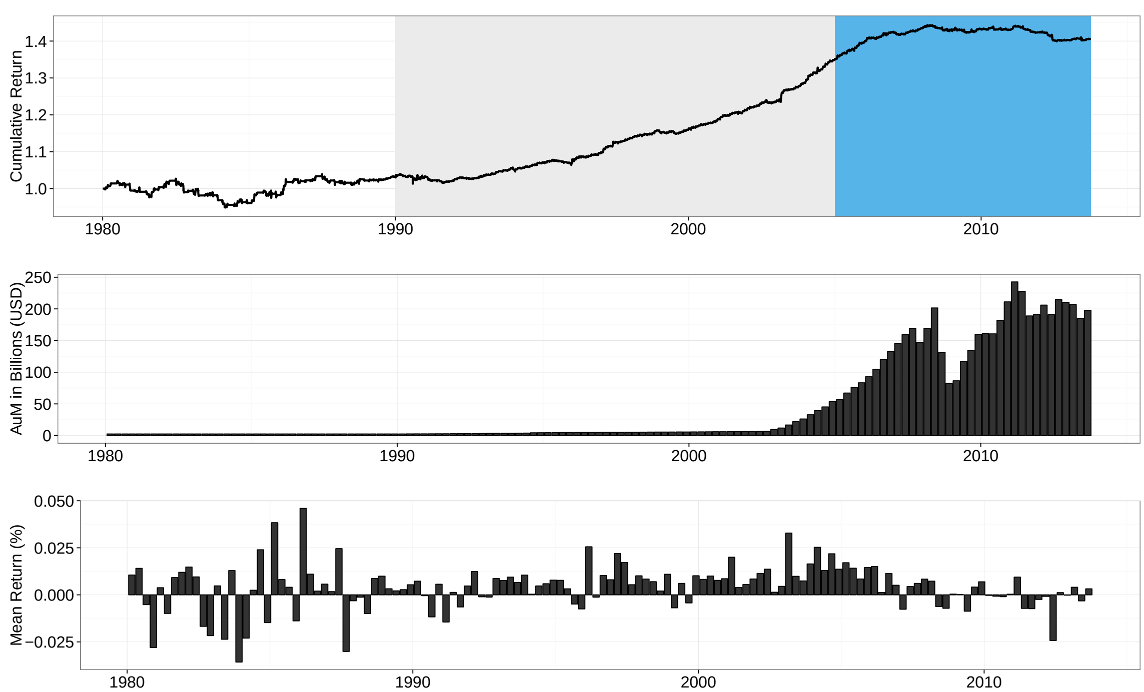


Figure 6: The Goldman Roll has Ceased



B Tables

Table 1: Commodity Futures Employed in the Strategy
Guide to the Nearby Contract throughout the Year, List of Dates of Contracts in the Sample, and Their Trading Venues

Exchange	Commodity	Symbol	Futures Data	Traded contract as of beginning of Month 1	2	3	4	5	6	7	8	9	10	11	12
			Grains												
CBOT	Corn	C	1990 - 2013	H	K	K	N	N	U	U	Z	Z	Z	H	H
CBOT	Wheat	W	1990 - 2013	H	K	K	N	N	U	U	Z	Z	Z	H	H
CBOT	Soybeans	S	1990 - 2013	H	K	K	N	N	X	X	X	X	F	F	H
CBOT	Soybean Meal	SM	1990 - 2013	H	K	K	N	N	Z	Z	Z	Z	Z	F	H
			Softs												
ICE (CSCE)	Cocoa	CC	1990 - 2013	H	K	K	N	N	U	U	Z	Z	Z	H	H
ICE (CSCE)	Cotton	CT	1990 - 2013	H	K	K	N	N	Z	Z	Z	Z	Z	H	H
ICE (CSCE)	Coffee	KC	1990 - 2013	H	K	K	N	N	U	U	Z	Z	Z	H	H
ICE (NYBOT)	Sugar	SB	1990 - 2013	H	K	K	N	N	V	V	V	H	H	H	H
			Energy												
NYMEX	Crude Oil	CL	1990 - 2013	H	J	K	M	N	Q	U	V	X	Z	F	G
NYMEX	Natural Gas	NG	1990 - 2013	H	J	K	M	N	Q	U	V	X	Z	F	G
NYMEX	Heating Oil	HO	1990 - 2013	H	J	K	M	N	Q	U	V	X	Z	F	G
NYMEX	Gasoline (RBOB)	RB	1990 - 2013	H	J	K	M	N	Q	U	V	X	Z	F	G
			Meats												
CME	Feeder Cattle	FC	1990 - 2013	H	J	K	Q	Q	Q	U	V	X	F	F	H
CME	Live Hogs	LH	1990 - 2013	J	J	M	M	N	U	V	V	Z	Z	G	G
CME	Live Cattle	LC	1990 - 2013	J	J	M	M	U	U	V	V	Z	Z	G	G
			Metals												
COMEX	Copper	HG	1990 - 2013	H	K	K	N	N	U	U	Z	Z	Z	H	H
COMEX	Silver	SI	1990 - 2013	H	K	K	N	N	U	U	Z	Z	Z	H	H
COMEX	Gold	GC	1990 - 2013	J	J	M	M	U	U	Z	Z	Z	Z	G	G
NYMEX	Platinum	PL	1990 - 2013	J	J	N	N	N	V	V	V	F	F	F	J
			Control												
CBOT	Soybean Oil	BO	1990 - 2013	H	K	K	N	N	Z	Z	Z	Z	Z	F	H
CBOT	Oats	O	1990 - 2013	H	K	K	N	N	U	U	Z	Z	Z	H	H
CBOT	Rough Rice	RR	1990 - 2013	H	K	K	N	N	U	U	Z	Z	Z	H	H
ICE US (NYCE)	Frozen Orange Juice	OJ	1990 - 2013	H	K	K	N	N	U	U	X	X	F	F	H
CME	Lumber	LB	1990 - 2013	H	K	K	N	N	U	U	X	X	F	F	H
NYMEX	Palladium	PA	1990 - 2013	H	M	M	M	U	U	U	Z	Z	Z	H	H
NYMEX	Platinum	PL	1990 - 2013	J	J	N	N	N	V	V	V	F	F	F	J

CBOT: Chicago Board of Trade, ICE: Intercontinental Exchange, CSCE: Coffee, Sugar and Cocoa Exchange, NYMEX: New York Mercantile Exchange, CME: Chicago Mercantile Exchange, COMEX: Commodity Exchange F: January, G: February, H: March, J: April, K: May, M: June, N: July, Q: August, U: September, V: October, X: November, Z: December

Table 2: Summary Statistics of Monthly Percentage Returns (annualized)

This table reports summary statistics for our trend following strategy. The strategy is long a year spread if the "nearby-next-out spread" is above its 50 day moving average and short a year spread if the "nearby-next-out spread" is below its 50 day moving average. All statistics are estimated from monthly data and then annualized. The minimum and maximum, which are the "worst" and the "best" month. An overview of the individual commodities and their group membership is given in Table 1.

	Grains	Softs	Energy	Meats	Metals	Portfolio	Control
1990 - 2013							
Mean	3.87	4.08	5.92	2.72	1.28	3.73	-1.41
Volatility	7.66	7.11	12.39	7.84	3.10	4.09	5.36
Sharpe Ratio	0.51	0.57	0.48	0.35	0.41	0.91	-0.26
Skewness	0.35	-0.65	0.69	0.95	0.24	0.34	-0.44
Kurtosis	5.40	7.98	4.73	5.23	5.75	4.28	3.80
Minimum	-7.69	-12.09	-10.04	-5.67	-3.19	-3.66	-6.55
Maximum	10.18	7.12	14.00	11.37	4.10	4.89	3.77
1990 - 2004							
Mean	1.13	2.87	2.51	3.16	0.61	2.05	-2.14
Volatility	7.30	7.76	13.62	7.62	3.53	4.24	5.47
Sharpe Ratio	0.15	0.37	0.18	0.41	0.17	0.48	-0.39
Skewness	0.16	-0.95	0.75	1.07	0.30	0.46	-0.60
Kurtosis	7.21	7.91	4.64	6.43	4.97	5.09	4.22
Minimum	-7.69	-12.09	-10.04	-5.67	-3.19	-3.66	-6.55
Maximum	10.18	7.12	14.00	11.37	4.10	4.89	3.63
2005 - 2013							
Mean	8.45	6.12	11.59	1.98	2.40	6.54	-0.18
Volatility	8.08	5.85	9.86	8.22	2.20	3.72	5.18
Sharpe Ratio	1.05	1.04	1.18	0.24	1.09	1.76	-0.03
Skewness	0.51	0.78	0.83	0.80	0.44	0.26	-0.11
Kurtosis	3.18	4.48	3.89	3.67	6.35	2.40	2.73
Minimum	-3.84	-3.52	-4.70	-4.74	-2.05	-1.90	-3.60
Maximum	7.07	6.59	10.99	7.61	2.53	3.13	3.77

Table 3: Factor Regression Results for Portfolio

Returns on Common Risk Factors by Time Period: mkt, smb, hml, and umd denote the market, size, value, and momentum factor for equities from Kenneth French's website (Fama and French (1992) and Jegadeesh and Titman (1993)), liq denotes the Pastor and Stambaugh (2003) liquidity factor, val, mom, and tsmom denote the commodity value, commodity momentum and commodity time series momentum factors of Asness, Moskowitz, and Pedersen (2013) and Moskowitz, Ooi, and Pedersen (2012), Newey and West (1987) standard errors in parenthesis.

	Monthly Excess Return (%)											
	1990-2013				1990-2004				2005-2013			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
alpha	0.326***	0.360***	0.325***	0.311***	0.176**	0.180**	0.115	0.106	0.561***	0.669***	0.664***	0.642***
	(0.073)	(0.075)	(0.073)	(0.071)	(0.082)	(0.085)	(0.089)	(0.087)	(0.125)	(0.118)	(0.131)	(0.118)
mkt	−0.021	−0.019	−0.008		−0.021	−0.020	−0.006		−0.020	−0.003	−0.012	
	(0.019)	(0.020)	(0.017)		(0.028)	(0.028)	(0.023)		(0.029)	(0.027)	(0.025)	
smb	0.025	0.024			0.029	0.029*			−0.022	−0.021		
	(0.018)	(0.017)			(0.018)	(0.017)			(0.049)	(0.053)		
hml	−0.015	−0.018			−0.017	−0.016			0.010	−0.013		
	(0.023)	(0.024)			(0.028)	(0.027)			(0.045)	(0.047)		
umd	−0.007	−0.006			0.008	0.007			−0.022	−0.013		
	(0.014)	(0.014)			(0.016)	(0.017)			(0.017)	(0.020)		
liq		−0.018	−0.018			−0.007	−0.010			−0.024	−0.037	
		(0.019)	(0.020)			(0.027)	(0.026)			(0.032)	(0.025)	
val			0.003	0.004			0.017	0.016			−0.024	−0.015
			(0.013)	(0.013)			(0.015)	(0.016)			(0.020)	(0.023)
mom			0.022	0.023			0.023	0.023			0.014	0.016
			(0.019)	(0.018)			(0.025)	(0.024)			(0.030)	(0.032)
tsmom			0.006	0.005			0.024	0.025			0.001	−0.004
			(0.022)	(0.022)			(0.034)	(0.034)			(0.028)	(0.029)
Adjusted R^2	-0.004	-0.006	-0.001	0.002	-0.006	-0.011	0.0001	0.010	-0.022	-0.037	-0.016	-0.018

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4: Factor Regression Results for Portfolio

Returns on Extended Risk Factors by Time Period: vix denotes the implied volatility index, rv denotes realized volatility, bond, fx, com, ir and stock are the trend-following factors of Fung and Hsieh (2001), l-or, h-or, l-spread, h-spread, l-amihud and h-amihud are the commodity factors of Szymanowska, De Roon, Nijman, and van den Goorbergh (2014). l-or (h-or) are the portfolio returns of outright contracts sorted on the basis, l-spread (h-spread) are the portfolio returns of calendar spreads sorted on the basis, l-amihud (h-amihud) are the portfolio returns of outright contracts sorted on the Amihud (2002) illiquidity measure. Newey and West (1987) standard errors in parenthesis.

	Monthly Excess Return (%)								
	1990-2013			1990-2004			2005-2013		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
alpha	0.512*	0.360***	0.380***	−0.141	0.213*	0.320***	1.163***	0.530***	0.444***
	(0.278)	(0.086)	(0.082)	(0.294)	(0.120)	(0.116)	(0.436)	(0.155)	(0.118)
vix	−0.014			0.022			−0.040*		
	(0.014)			(0.017)			(0.023)		
rv	0.312			−0.594			0.541**		
	(0.199)			(0.509)			(0.244)		
bond		−0.009*			−0.004			−0.013	
		(0.005)			(0.006)			(0.009)	
fx		−0.005			−0.008			0.002	
		(0.004)			(0.007)			(0.005)	
com		0.006			0.013			−0.002	
		(0.006)			(0.011)			(0.006)	
ir		0.002			0.006			−0.0001	
		(0.004)			(0.008)			(0.004)	
stk		0.006			0.004			0.006	
		(0.005)			(0.009)			(0.008)	
l-or			−0.003			−0.031			0.006
			(0.034)			(0.046)			(0.044)
h-or			0.112***			0.119**			0.039
			(0.034)			(0.052)			(0.040)
l-spread			0.054			0.027			0.111**
			(0.037)			(0.044)			(0.052)
h-spread			0.049			0.044			0.050
			(0.041)			(0.054)			(0.076)
l-amihud			0.011			−2.793			11.165
			(6.392)			(7.579)			(12.142)
h-amihud			−9.253			−3.647			−13.422
			(6.488)			(7.797)			(12.858)
Adjusted R^2	0.0001	0.001	0.047	-0.005	-0.005	0.035	0.028	-0.014	0.043

Note: *p<0.1; **p<0.05; ***p<0.01

Table 5: Active-Passive Decomposition of Returns by Group (1990-2013)
This table provides a decomposition of the total return into an active and a passive component. The passive component can be understood as a compensation for risk bearing, whereas the active component represents timing-skill. The active-passive decomposition is detailed in Lo (2008).

	Annualized (%)				
	$E[R_{pt}]$	Active	Passive	% Active	SE (%) (AR)
Control	-1.32	-1.83	0.51	163.19	2.17
Grains	3.85	2.80	1.05	78.62	2.61
Softs	4.17	3.96	0.21	95.18	1.79
Energy	5.54	4.65	0.90	86.08	1.67
Meats	2.71	2.58	0.13	95.29	0.37
Metals	1.28	1.25	0.02	98.22	1.97

Table 6: Breakdown of Percentage Returns by Position Type and by Leg (1990-2013)
In this table, we decompose the total return into a contribution from long and short positions (in spreads). We also show the contributions from the front leg and back separately. We then additionally show the contribution of the front and back leg separately for long and short positions in spreads.

	Spread Return			**Leg Return**		**Long Spread**		**Short Spread**	
	Total	Long	Short	Front	Back	Front	Back	Front	Back
Control	-32.34	-43.41	11.07	8.63	-40.82	-5.19	-38.08	14.13	-3.05
Energy	138.71	34.32	104.39	215.65	-78.69	181.21	-148.64	34.43	69.95
Grains	92.34	23.78	68.56	98.92	-6.58	67.77	-43.99	31.15	37.41
Meats	65.17	-25.88	91.05	-4.43	69.60	-18.12	-7.76	13.69	77.36
Metals	30.51	16.11	14.40	72.54	-42.03	112.31	-96.20	-39.77	54.17
Softs	98.88	36.39	62.49	48.14	50.74	26.99	9.40	21.15	41.34

Table 7: Volatility Reduction from Trading Spreads (1990-2013)
This table compares the total spread volatility to the volatility of the component legs of the spreads and displays the correlation between the front leg (held long) and the back leg (held short).

	Ann. Volatility (%)			
	Total	Front Leg	Back Leg	Correlation
Grains	7.66	15.80	11.67	-0.88
Softs	7.11	15.57	12.19	-0.90
Energy	12.39	20.31	12.04	-0.81
Meats	7.84	9.62	5.86	-0.59
Metals	3.10	15.68	14.62	-0.98
Control	5.36	10.87	8.43	-0.87

Table 8: Autocorrelation of the Front Leg Return
This table shows the regression results to the following specification:
$R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_2 I(year \geq 2005) + \beta_3 I(year \geq 2005) \times R_{i,t-1} + \varepsilon_{i,t}$, where $R_{i,t}$ denotes the daily percentage return of the nearby futures contract (the front leg of a year spread). This specification presents a test for an increase in first order autocorrelation. Standard errors are clustered at the commodity market level.

	Grains	Softs	Energy	Meats	Metals	Control
(Intercept)	-0.0072	0.0011	0.0518^{***}	0.0033	0.0086	-0.0020
	(0.0113)	(0.0078)	(0.0094)	(0.0021)	(0.0089)	(0.0102)
$R_{i,t-1}$	0.0212^{*}	-0.0014	-0.0064	0.0373^{***}	-0.0307^{***}	0.0697^{***}
	(0.0124)	(0.0031)	(0.0115)	(0.0023)	(0.0066)	(0.0129)
$I(year \geq 2005)$	0.0377^{***}	0.0012	-0.0705^{**}	-0.0236^{*}	0.0480^{***}	0.0013
	(0.0077)	(0.0104)	(0.0306)	(0.0128)	(0.0090)	(0.0126)
$I(year \geq 2005) \times R_{i,t-1}$	-0.0030	0.0093	-0.0226^{*}	-0.0149	-0.0078	0.0002
	(0.0119)	(0.0149)	(0.0124)	(0.0216)	(0.0135)	(0.0172)
Adj. R^2	0.0005	0.0000	0.0006	0.0012	0.0015	0.0049

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 9: Autocorrelation of the Back Leg Return

This table shows the regression results to the following specification:
$R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_2 I(year \geq 2005) + \beta_3 I(year \geq 2005) \times R_{i,t-1} + \varepsilon_{i,t}$, where $R_{i,t}$ denotes the daily percentage return of a futures contract with one year to expiry (the back leg of a year spread). This specification presents a test for an increase in first order autocorrelation. Standard errors are clustered at the commodity market level.

	Grains	Softs	Energy	Meats	Metals	Control
(Intercept)	-0.0003	-0.0034^{*}	0.0496^{***}	0.0050^{*}	0.0045	-0.0002
	(0.0020)	(0.0019)	(0.0027)	(0.0027)	(0.0069)	(0.0086)
$R_{i,t-1}$	-0.0105^{***}	-0.0283^{***}	-0.0706^{***}	0.0562^{***}	-0.0479^{**}	0.0353^{**}
	(0.0034)	(0.0055)	(0.0172)	(0.0175)	(0.0211)	(0.0171)
$I(year \geq 2005)$	0.0403^{***}	0.0245^{**}	-0.0269	0.0223^{***}	0.0584^{***}	0.0185^{**}
	(0.0053)	(0.0100)	(0.0192)	(0.0027)	(0.0036)	(0.0089)
$I(year \geq 2005) \times R_{i,t-1}$	-0.0188^{**}	0.0077	0.0310^{**}	0.0163	0.0108^{**}	0.0160
	(0.0096)	(0.0071)	(0.0145)	(0.0197)	(0.0045)	(0.0158)
Adj. R^2	0.0008	0.0007	0.0035	0.0044	0.0021	0.0019

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 10: Autocorrelation of Year Spread Returns

This table shows the regression results to the following specification:
$R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_2 I(year \geq 2005) + \beta_3 I(year \geq 2005) \times R_{i,t-1} + \varepsilon_{i,t}$, where $R_{i,t}$ denotes the daily percentage return of a year spread. This specification presents a test for an increase in first order autocorrelation. Standard errors are clustered at the commodity market level.

	Grains	Softs	Energy	Meats	Metals	Control
(Intercept)	-0.0070	0.0044	0.0040	-0.0018	0.0037^{*}	-0.0024
	(0.0099)	(0.0065)	(0.0106)	(0.0049)	(0.0021)	(0.0034)
$R_{i,t-1}$	-0.0028	-0.0305^{**}	0.0583^{**}	0.0550^{***}	0.0469^{***}	-0.0397^{*}
	(0.0248)	(0.0151)	(0.0288)	(0.0137)	(0.0024)	(0.0218)
$I(year \geq 2005)$	0.0001	-0.0211^{**}	-0.0418^{***}	-0.0470^{***}	-0.0096	-0.0177^{***}
	(0.0038)	(0.0092)	(0.0132)	(0.0084)	(0.0062)	(0.0058)
$I(year \geq 2005) \times R_{i,t-1}$	0.1143^{***}	0.1193^{***}	-0.0040	-0.0269^{*}	0.0026	0.0441^{**}
	(0.0211)	(0.0117)	(0.0118)	(0.0145)	(0.0097)	(0.0182)
Adj. R^2	0.0052	0.0029	0.0036	0.0030	0.0025	0.0010

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 11: Autocorrelation in Year Spread Returns as a Function of Money Managers' Positions

This table shows the regression results to the following specification:
$R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \beta_2 \text{Money Managers}_{i,t-1} + \beta_3 \text{Money Managers}_{i,t-1} \times R_{i,t-1} + \varepsilon_{i,t}$, where $R_{i,t}$ denotes the daily percentage return of a year spread, Money Managers$_{i,t-1}$ denotes the net long position of money managers at time $t-1$. Through this specification we make the coefficient of first order autocorrelation a function of money managers positions. Standard errors are clustered at the commodity market level.

	Grains	Softs	Energy	Meats	Metals	Control
(Intercept)	-0.0009	-0.0043	-0.0243	-0.0173	0.0011^{***}	-0.0035
	(0.0059)	(0.0037)	(0.0150)	(0.0122)	(0.0004)	(0.0043)
$R_{i,t-1}$	0.0046	0.0082	0.0443^{**}	0.0586^{***}	0.0468^{***}	-0.0184^{*}
	(0.0096)	(0.0222)	(0.0188)	(0.0045)	(0.0012)	(0.0100)
Money Managers$_{i,t-1}$	-0.0010^{*}	-0.0003	0.0022^{**}	-0.0001	-0.0001	-0.0003^{*}
	(0.0006)	(0.0002)	(0.0010)	(0.0006)	(0.0001)	(0.0002)
Money Managers$_{i,t-1} \times R_{i,t-1}$	0.0063^{***}	0.0029^{***}	0.0059^{***}	-0.0018	0.0032^{***}	-0.0003
	(0.0006)	(0.0008)	(0.0006)	(0.0012)	(0.0006)	(0.0006)
Adj. R^2	0.0056	0.0017	0.0053	0.0023	0.0026	0.0005

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 12: Counterfactual Autocorrelation in Year Spread Returns

This table shows the regression results to the following specification:
$R_{i,t} = \alpha + \beta_1 R_{i,t-1} + \varepsilon_{i,t}$, where $R_{i,t}$ denotes the daily percentage return of a year spread. The estimation is done over the same period as in Table 11 and thus presents the counterfactual estimate if the money managers had not been active. Standard errors are clustered at the commodity market level.

	Grains	Softs	Energy	Meats	Metals	Control
(Intercept)	-0.0068	-0.0168^{***}	-0.0378^{*}	-0.0488^{***}	-0.0059	-0.0201^{***}
	(0.0088)	(0.0035)	(0.0209)	(0.0108)	(0.0043)	(0.0069)
$R_{i,t-1}$	0.1116^{***}	0.0889^{***}	0.0543^{*}	0.0281	0.0494^{***}	0.0043
	(0.0072)	(0.0157)	(0.0317)	(0.0254)	(0.0114)	(0.0070)
Adj. R^2	0.0124	0.0079	0.0029	0.0008	0.0025	0.0000

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 13: Predictive Analysis

This table shows the regression results to the following specification:
$R_{i,t} = \alpha_i + \beta_1 R_{i,t-1} + \beta_2 \Delta OI_{i,t} + \beta_3 \text{Money Managers}_{i,t-1} + \varepsilon_{i,t}$, where $R_{i,t}$ denotes the weekly percentage return of our strategy, Money Managers$_{i,t-1}$ are the lagged net long positions of money managers and, $\Delta OI_{i,t}$ is the change in open interest from $t-1$ to t. This specification tests if money managers' positions help predict future returns to our strategy. Standard errors are clustered at the commodity market level.

	Grains	Softs	Energy	Meats	Metals	Control
R_{it-1}	0.0269	-0.0804^{***}	-0.0361	0.0421^{*}	0.0938^{***}	-0.0562^{***}
	(0.0222)	(0.0083)	(0.0403)	(0.0246)	(0.0066)	(0.0088)
$\Delta OI_{i,t}$	0.7492	-2.3243^{***}	2.1409	-2.4089	-0.1293^{***}	-0.9305
	(1.0287)	(0.5496)	(2.6772)	(2.9425)	(0.0372)	(0.6480)
Money Managers$_{i,t-1}$	0.0144^{*}	0.0077^{*}	0.0065	-0.0002	0.0019^{**}	0.0012
	(0.0087)	(0.0041)	(0.0088)	(0.0036)	(0.0008)	(0.0031)
Adj. R^2	0.0050	0.0105	0.0026	0.0040	0.0115	0.0037

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 14: Regression on the Trading Strategy's Excess Return:

This tables shows the results from regression the strategy's quarterly returns.
Abnormal Spreading$_{i,t}$ denotes average the percentage of open interest in spreads by non-commerical market participants for a given quarter, Slope$_{i,t}$ denotes the average of $\ln F_{n_2,t} - \ln F_{n_1,t}$ for a given quarter, Inflation and GDP Growth are also calculated for this quarter, VIX denotes the implied volatility index. The sample period is 1990 to 2013.

	Quarterly Excess Return (%)					
	All Commodities		Treated Commodities		Control	
	(1)	(2)	(3)	(4)	(5)	(6)
(Intercept)	0.466		0.504		0.237	-0.026
	(0.329)		(0.416)		(0.235)	(0.058)
Abnormal Spreading$_{i,t}$	0.040^{***}	0.040^{***}	0.043^{***}	0.048^{***}	0.018	0.015
	(0.012)	(0.014)	(0.010)	(0.015)	(0.013)	(0.012)
Long Return$_{i,t}$	-0.677	-0.583	-0.849	-0.808	-0.132	-0.281
	(0.466)	(0.529)	(0.577)	(0.619)	(0.394)	(0.421)
Slope$_{i,t}$	8.716^{*}	8.087^{*}	10.430^{*}	9.499^{*}	0.451	1.562
	(4.782)	(4.592)	(5.416)	(5.001)	(5.389)	(5.174)
Inflation$_t$	-6.363		-12.800		17.929	
	(10.823)		(10.054)		(14.075)	
GDP Growth$_t$	-10.335		-1.310		-34.320^{**}	
	(12.989)		(14.689)		(16.221)	
VIX$_t$	-0.014		-0.015		-0.008	
	(0.012)		(0.016)		(0.012)	
Adjusted R^2	0.028	0.020	0.032	0.023	0.016	0.004

Note: *p<0.1; **p<0.05; ***p<0.01

Table 15: Open Interest Term Structure

This table shows the regression results to the following specification:

$100\times\frac{OI_{n_i,j,t}}{OI_{n_1,j,t}} = \alpha+\beta_1 n_{i,j,t}+\beta_2 I(year \geq 2005)+\beta_3 I(year \geq 2005)\times n_{i,j,t}+\text{Monthly Dummies}+\varepsilon_{i,j,t}$

$OI_{n_i,j,t}$ denotes the open interest (in number of contracts) for a contract with time to maturity n_i for day t and commodity j and $n_{i,j,t}$ denotes the time to delivery in years. We include delivery month dummies to capture the effect of seasonalities in some commdities. Standard errors are clustered at the commodity market level.

	Grains	Softs	Energy	Meats	Metals	Control
(Intercept)	29.131***	36.915***	7.992***	33.854***	14.825***	41.606***
	(4.744)	(4.133)	(1.118)	(5.163)	(4.725)	(5.758)
Maturity	−29.845***	−26.797***	−2.544***	−47.857***	−7.389***	−48.049***
	(4.414)	(3.994)	(0.371)	(7.110)	(2.149)	(7.247)
Post 2004	−10.545***	−7.623***	−1.981***	−2.663	0.774	−15.213***
	(1.485)	(1.950)	(0.454)	(1.912)	(1.185)	(2.492)
Post 2004 x Maturity	15.439***	11.045***	0.859***	7.178**	−0.576	29.129***
	(2.813)	(2.257)	(0.181)	(3.447)	(0.569)	(5.016)
Adj. R^2	0.560	0.552	0.261	0.650	0.274	0.443

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 16: Shape of the Term Structure

This table shows the regression results to the following specification:

$100 \times \frac{F_{n_i,j,t}}{F_{n_1,j,t}} = \alpha + \beta_1 n_{i,j,t} + \beta_2 n^2_{i,j,t} + \varepsilon_{i,j,t}$

$F_{n_i,j,t}$ denotes the futures price for a contract with time to maturity n_i for day t and commodity j and ni, j, t denotes the time to delivery in years. We include delivery month dummies to capture the effect of seasonalities in some commdities. Standard errors are clustered at the commodity market level.

	Grains	Softs	Energy	Meats	Metals	Control
(Intercept)	102.499***	100.262***	96.578***	99.527***	102.456***	96.086***
	(1.062)	(1.026)	(0.518)	(0.401)	(0.846)	(1.142)
Maturity	2.863**	8.038***	3.490***	1.488	0.461	7.041***
	(1.425)	(1.858)	(0.470)	(1.692)	(0.816)	(1.338)
$(\text{Maturity})^2$	−0.909**	−2.338***	−0.562***	−0.480	0.584***	−0.609
	(0.394)	(0.697)	(0.095)	(1.529)	(0.171)	(0.566)
Adj. R^2	0.102	0.130	0.038	0.004	0.523	0.206

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 17: Volatility Term Structure

This table shows the regression results to the following specification:
$100 \times \frac{\sigma_{n_i,j,t}}{\sigma_{n_1,j,t}} = \alpha + \beta_1 n_{i,j,t} + \beta_2 I(year \geq 2005) + \beta_3 I(year \geq 2005) \times n_{i,j,t} + \text{Monthly Dummies} + \varepsilon_{i,j,t}$
$\sigma_{n_i,j,t}$ denotes the monthly volatility for a contract with time to maturity n_i for month t and commodity j and $n_{i,j,t}$ denotes the time to delivery in years. We include delivery month dummies to capture the effect of seasonalities in some commdities. Standard errors are clustered at the commodity market level.

	Grains	Softs	Energy	Meats	Metals	Control
(Intercept)	102.958***	105.663***	95.621***	102.433***	102.606***	103.437***
	(1.035)	(2.133)	(2.116)	(2.049)	(1.385)	(1.503)
Maturity	−24.018***	−26.461***	−35.082***	−53.895***	−8.025***	−22.237***
	(1.138)	(2.938)	(3.156)	(2.877)	(2.615)	(2.821)
Post 2004	−0.872*	−0.015	2.637	0.006	0.320	0.115
	(0.526)	(0.614)	(1.742)	(0.758)	(1.273)	(0.584)
Post 2004 x Maturity	3.506***	8.355***	10.236***	9.808***	5.547*	3.945***
	(1.135)	(1.211)	(1.993)	(1.865)	(2.866)	(1.510)
Adj. R^2	0.371	0.489	0.502	0.546	0.419	0.336

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 18: Overlap with Front Running the Goldman Roll

This table shows the average percentage overlap with the positions of the front-running strategy for the Goldman Roll as detailed in Mou (2011). As illustrated in Figure 5, the possible overlap between our strategy and the front-running strategy is at most four days.

	Days with Same Position as Front Running (%)					
	Grains	Softs	Energy	Meats	Metals	Control
Pre 2005	56.5	56.4	56.7	46.3	55.7	52.2
Post 2005	62.2	70.9	60.3	71.1	70.0	60.5

C Robustness, Additional Tables and Figures

Table 19: Factor Regression Results for Grains

Returns on Common Risk Factors by Time Period: mkt, smb, hml, and umd denote the market, size, value, and momentum factor for equities from Kenneth French's website (Fama and French (1992) and Jegadeesh and Titman (1993)), liq denotes the Pastor and Stambaugh (2003) liquidity factor, val, mom, and tsmom denote the commodity value, commodity momentum and commodity time series momentum factors of Asness, Moskowitz, and Pedersen (2013) and Moskowitz, Ooi, and Pedersen (2012), Newey and West (1987) standard errors in parenthesis.

	Monthly Excess Return (%)											
	1990-2013				1990-2004				2005-2013			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
alpha	0.361***	0.384***	0.406***	0.390**	0.109	0.078	−0.032	−0.022	0.757***	0.883***	0.941***	0.928***
	(0.130)	(0.134)	(0.152)	(0.169)	(0.150)	(0.152)	(0.168)	(0.164)	(0.216)	(0.198)	(0.253)	(0.254)
mkt	−0.061**	−0.054**	−0.044*		−0.053*	−0.056*	−0.037		−0.109*	−0.085	−0.025	
	(0.026)	(0.027)	(0.026)		(0.031)	(0.032)	(0.023)		(0.057)	(0.053)	(0.039)	
smb	0.042	0.042			0.029	0.031			0.017	−0.023		
	(0.032)	(0.032)			(0.031)	(0.032)			(0.095)	(0.102)		
hml	0.028	0.036			0.003	0.002			0.142	0.178		
	(0.036)	(0.037)			(0.047)	(0.046)			(0.090)	(0.111)		
umd	−0.029	−0.027			0.011	0.015			−0.077*	−0.073		
	(0.032)	(0.031)			(0.025)	(0.026)			(0.040)	(0.046)		
liq		0.027	0.019			0.059	0.068*			0.041	−0.013	
		(0.031)	(0.030)			(0.038)	(0.041)			(0.060)	(0.048)	
val			−0.041*	−0.042*			−0.047	−0.046			−0.052	−0.046
			(0.024)	(0.024)			(0.030)	(0.030)			(0.047)	(0.043)
mom			0.00002	0.0004			−0.037	−0.033			−0.002	−0.004
			(0.033)	(0.032)			(0.034)	(0.035)			(0.069)	(0.073)
tsmom			−0.012	−0.009			0.135**	0.133**			−0.120**	−0.121**
			(0.047)	(0.051)			(0.065)	(0.060)			(0.052)	(0.049)
Adjusted R^2	0.004	-0.001	0.002	0.0002	-0.008	-0.002	0.051	0.042	0.026	0.004	0.004	0.023

Note: *p<0.1; **p<0.05; ***p<0.01

Table 20: Factor Regression Results for Softs

Returns on Common Risk Factors by Time Period: mkt, smb, hml, and umd denote the market, size, value, and momentum factor for equities from Kenneth French's website (Fama and French (1992) and Jegadeesh and Titman (1993)), liq denotes the Pastor and Stambaugh (2003) liquidity factor, val, mom, and tsmom denote the commodity value, commodity momentum and commodity time series momentum factors of Asness, Moskowitz, and Pedersen (2013) and Moskowitz, Ooi, and Pedersen (2012), Newey and West (1987) standard errors in parenthesis.

	Monthly Excess Return (%)											
	1990-2013				1990-2004				2005-2013			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
alpha	0.323**	0.372***	0.365**	0.375**	0.206	0.216	0.247	0.285	0.491***	0.642***	0.604***	0.568***
	(0.143)	(0.142)	(0.154)	(0.153)	(0.198)	(0.213)	(0.235)	(0.232)	(0.174)	(0.187)	(0.198)	(0.187)
mkt	0.041	0.043	0.057*		0.050	0.051	0.066*		0.081	0.109**	0.033	
	(0.031)	(0.031)	(0.030)		(0.042)	(0.041)	(0.035)		(0.051)	(0.050)	(0.055)	
smb	0.027	0.023			0.066*	0.065**			−0.129**	−0.099		
	(0.029)	(0.031)			(0.035)	(0.032)			(0.057)	(0.065)		
hml	−0.040	−0.049			−0.005	−0.004			−0.058	−0.151**		
	(0.039)	(0.040)			(0.058)	(0.057)			(0.063)	(0.061)		
umd	−0.006	−0.004			−0.013	−0.015			0.010	0.035		
	(0.021)	(0.021)			(0.027)	(0.026)			(0.028)	(0.027)		
liq		−0.048*	−0.046			−0.019	−0.021			−0.117**	−0.091**	
		(0.028)	(0.029)			(0.038)	(0.036)			(0.046)	(0.041)	
val			−0.016	−0.015			−0.016	−0.013			−0.016	−0.003
			(0.023)	(0.022)			(0.028)	(0.028)			(0.030)	(0.037)
mom			−0.009	−0.009			−0.012	−0.014			0.016	0.026
			(0.033)	(0.033)			(0.042)	(0.043)			(0.053)	(0.056)
tsmom			0.00001	−0.004			−0.014	−0.019			0.028	0.013
			(0.036)	(0.037)			(0.058)	(0.059)			(0.045)	(0.046)
Adjusted R^2	0.007	0.011	0.005	-0.009	0.007	0.002	-0.008	-0.013	0.004	0.072	0.020	-0.021

Note: *p<0.1; **p<0.05; ***p<0.01

Table 21: Factor Regression Results for Energy

Returns on Common Risk Factors by Time Period: mkt, smb, hml, and umd denote the market, size, value, and momentum factor for equities from Kenneth French's website (Fama and French (1992) and Jegadeesh and Titman (1993)), liq denotes the Pastor and Stambaugh (2003) liquidity factor, val, mom, and tsmom denote the commodity value, commodity momentum and commodity time series momentum factors of Asness, Moskowitz, and Pedersen (2013) and Moskowitz, Ooi, and Pedersen (2012), Newey and West (1987) standard errors in parenthesis.

	Monthly Excess Return (%)											
	1990-2013				1990-2004				2005-2013			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
alpha	0.514**	0.568**	0.499**	0.447**	0.205	0.229	0.160	0.086	1.002***	1.132***	1.101***	1.049***
	(0.232)	(0.244)	(0.222)	(0.220)	(0.300)	(0.304)	(0.294)	(0.287)	(0.347)	(0.387)	(0.346)	(0.352)
mkt	−0.053	−0.053	−0.038		−0.067	−0.065	−0.052		−0.032	−0.020	−0.028	
	(0.056)	(0.058)	(0.051)		(0.093)	(0.096)	(0.075)		(0.062)	(0.065)	(0.050)	
smb	0.055	0.054			0.063	0.061			−0.105	−0.077		
	(0.058)	(0.057)			(0.059)	(0.060)			(0.141)	(0.157)		
hml	−0.003	−0.014			−0.025	−0.024			0.066	0.018		
	(0.077)	(0.079)			(0.101)	(0.103)			(0.142)	(0.154)		
umd	0.001	0.0003			0.045	0.042			−0.056	−0.049		
	(0.041)	(0.041)			(0.051)	(0.055)			(0.050)	(0.062)		
liq		−0.065	−0.062			−0.045	−0.062			−0.054	−0.087	
		(0.059)	(0.059)			(0.099)	(0.093)			(0.079)	(0.060)	
val			0.052	0.054			0.086	0.079			−0.002	0.019
			(0.049)	(0.050)			(0.065)	(0.065)			(0.066)	(0.076)
mom			0.094	0.096			0.095	0.094			0.101	0.104
			(0.064)	(0.064)			(0.078)	(0.080)			(0.104)	(0.093)
tsmom			−0.029	−0.032			−0.022	−0.011			−0.027	−0.039
			(0.064)	(0.062)			(0.099)	(0.102)			(0.078)	(0.080)
Adjusted R^2	-0.009	-0.008	0.003	0.004	-0.009	-0.013	-0.002	0.002	-0.019	-0.032	-0.019	-0.015

Note: *p<0.1; **p<0.05; ***p<0.01

Table 22: Factor Regression Results for Meats

Returns on Common Risk Factors by Time Period: mkt, smb, hml, and umd denote the market, size, value, and momentum factor for equities from Kenneth French's website (Fama and French (1992) and Jegadeesh and Titman (1993)), liq denotes the Pastor and Stambaugh (2003) liquidity factor, val, mom, and tsmom denote the commodity value, commodity momentum and commodity time series momentum factors of Asness, Moskowitz, and Pedersen (2013) and Moskowitz, Ooi, and Pedersen (2012), Newey and West (1987) standard errors in parenthesis.

	Monthly Excess Return (%)											
	1990-2013				1990-2004				2005-2013			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
alpha	0.256^{*}	0.284^{*}	0.177	0.185	0.311^{*}	0.317^{*}	0.182	0.183	0.165	0.266	0.253	0.254
	(0.155)	(0.164)	(0.155)	(0.155)	(0.188)	(0.192)	(0.169)	(0.169)	(0.299)	(0.322)	(0.284)	(0.272)
mkt	−0.019	−0.013	−0.001		−0.016	−0.015	0.010		−0.025	−0.005	−0.035	
	(0.038)	(0.039)	(0.037)		(0.059)	(0.058)	(0.053)		(0.061)	(0.069)	(0.048)	
smb	−0.010	−0.011			−0.024	−0.024			0.134	0.119		
	(0.049)	(0.052)			(0.049)	(0.051)			(0.103)	(0.112)		
hml	-0.068^{*}	-0.065^{*}			−0.055	−0.055			-0.145^{**}	-0.148^{*}		
	(0.038)	(0.038)			(0.053)	(0.053)			(0.070)	(0.082)		
umd	0.001	0.002			−0.016	−0.017			0.025	0.032		
	(0.027)	(0.028)			(0.029)	(0.029)			(0.058)	(0.061)		
liq		0.016	0.018			−0.011	−0.013			0.011	0.021	
		(0.028)	(0.028)			(0.036)	(0.035)			(0.047)	(0.048)	
val			0.011	0.011			0.047	0.048			−0.062	−0.062
			(0.027)	(0.027)			(0.032)	(0.032)			(0.057)	(0.056)
mom			0.014	0.014			0.069^{*}	0.068^{*}			−0.077	−0.082
			(0.033)	(0.033)			(0.037)	(0.038)			(0.055)	(0.056)
tsmom			0.068	0.068^{*}			−0.012	−0.011			0.144^{**}	0.148^{**}
			(0.042)	(0.042)			(0.053)	(0.058)			(0.065)	(0.065)
Adjusted R^2	-0.006	-0.010	0.004	0.010	-0.017	-0.023	0.0001	0.011	0.003	-0.011	0.032	0.048

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 23: Factor Regression Results for Metals

Returns on Common Risk Factors by Time Period: mkt, smb, hml, and umd denote the market, size, value, and momentum factor for equities from Kenneth French's website (Fama and French (1992) and Jegadeesh and Titman (1993)), liq denotes the Pastor and Stambaugh (2003) liquidity factor, val, mom, and tsmom denote the commodity value, commodity momentum and commodity time series momentum factors of Asness, Moskowitz, and Pedersen (2013) and Moskowitz, Ooi, and Pedersen (2012), Newey and West (1987) standard errors in parenthesis.

	Monthly Excess Return (%)											
	1990-2013				1990-2004				2005-2013			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
alpha	0.110**	0.116*	0.091	0.086	0.049	0.063	0.024	0.017	0.204***	0.210***	0.205***	0.208***
	(0.055)	(0.060)	(0.058)	(0.057)	(0.082)	(0.091)	(0.080)	(0.077)	(0.061)	(0.065)	(0.068)	(0.064)
mkt	−0.003	−0.003	−0.001		0.004	0.006	0.008		−0.021	−0.022	−0.013	
	(0.011)	(0.011)	(0.010)		(0.019)	(0.018)	(0.013)		(0.016)	(0.017)	(0.011)	
smb	0.0003	−0.00003			−0.004	−0.005			0.036	0.035		
	(0.015)	(0.015)			(0.018)	(0.017)			(0.032)	(0.034)		
hml	−0.005	−0.006			−0.002	−0.001			0.008	0.017		
	(0.014)	(0.015)			(0.023)	(0.025)			(0.025)	(0.029)		
umd	0.0001	0.0003			0.00001	−0.002			0.005	0.003		
	(0.006)	(0.006)			(0.008)	(0.008)			(0.010)	(0.013)		
liq		−0.008	−0.008			−0.026	−0.024			0.016	0.014	
		(0.014)	(0.014)			(0.021)	(0.024)			(0.013)	(0.013)	
val			0.004	0.005			0.004	0.004			0.012	0.012
			(0.008)	(0.008)			(0.012)	(0.011)			(0.011)	(0.012)
mom			0.003	0.004			0.001	0.0001			0.014	0.012
			(0.011)	(0.010)			(0.015)	(0.014)			(0.013)	(0.013)
tsmom			0.019	0.019			0.023	0.025			0.016	0.018
			(0.013)	(0.013)			(0.019)	(0.019)			(0.016)	(0.015)
Adjusted R^2	-0.014	-0.017	-0.008	-0.001	-0.022	-0.019	-0.011	-0.008	-0.015	-0.021	-0.005	-0.001

Note: *p<0.1; **p<0.05; ***p<0.01

Table 24: Factor Regression Results for Grains

Returns on Extended Risk Factors by Time Period: vix denotes the implied volatility index, rv denotes realized volatility, bond, fx, com, ir and stock are the trend-following factors of Fung and Hsieh (2001), l-or, h-or, l-spread, h-spread, l-amihud and h-amihud are the commodity factors of Szymanowska, De Roon, Nijman, and van den Goorbergh (2014). l-or (h-or) are the portfolio returns of outright contracts sorted on the basis, l-spread (h-spread) are the portfolio returns of calendar spreads sorted on the basis, l-amihud (h-amihud) are the portfolio returns of outright contracts sorted on the Amihud (2002) illiquidity measure. Newey and West (1987) standard errors in parenthesis.

	Monthly Excess Return (%)								
	1990-2013			1990-2004			2005-2013		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
alpha	0.567	0.442***	0.293**	−0.363	0.167	0.126	1.640**	0.672***	0.551**
	(0.499)	(0.155)	(0.141)	(0.598)	(0.189)	(0.166)	(0.791)	(0.239)	(0.255)
vix	−0.018			0.026			−0.058		
	(0.024)			(0.029)			(0.042)		
rv	0.434			−0.259			0.716		
	(0.280)			(0.625)			(0.449)		
bond		−0.018**			0.001			−0.033**	
		(0.008)			(0.009)			(0.013)	
fx		−0.012			−0.009			−0.010	
		(0.007)			(0.010)			(0.011)	
com		0.016			0.025			0.010	
		(0.013)			(0.019)			(0.018)	
ir		−0.004			−0.024**			0.004	
		(0.006)			(0.011)			(0.009)	
stk		0.018*			0.010			0.021	
		(0.010)			(0.009)			(0.016)	
l-or			0.054			0.025			0.079
			(0.066)			(0.081)			(0.094)
h-or			0.091			0.059			0.060
			(0.080)			(0.109)			(0.134)
l-spread			0.077			0.042			0.174
			(0.064)			(0.077)			(0.109)
h-spread			−0.009			0.001			−0.186
			(0.060)			(0.065)			(0.154)
l-amihud			10.946			11.467			11.223
			(16.186)			(18.524)			(25.297)
h-amihud			−29.068**			−24.428*			−28.923
			(11.689)			(13.336)			(20.127)
Adjusted R^2	-0.003	0.011	0.011	-0.008	0.016	-0.007	0.001	0.017	-0.002

Note: *p<0.1; **p<0.05; ***p<0.01

Table 25: Factor Regression Results for Softs

Returns on Extended Risk Factors by Time Period: vix denotes the implied volatility index, rv denotes realized volatility, bond, fx, com, ir and stock are the trend-following factors of Fung and Hsieh (2001), l-or, h-or, l-spread, h-spread, l-amihud and h-amihud are the commodity factors of Szymanowska, De Roon, Nijman, and van den Goorbergh (2014). l-or (h-or) are the portfolio returns of outright contracts sorted on the basis, l-spread (h-spread) are the portfolio returns of calendar spreads sorted on the basis, l-amihud (h-amihud) are the portfolio returns of outright contracts sorted on the Amihud (2002) illiquidity measure. Newey and West (1987) standard errors in parenthesis.

	Monthly Excess Return (%)								
	1990-2013			1990-2004			2005-2013		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
alpha	0.272	0.350**	0.534***	0.407	0.255	0.434**	0.286	0.505***	0.679***
	(0.556)	(0.150)	(0.141)	(0.861)	(0.244)	(0.173)	(0.523)	(0.165)	(0.201)
vix	−0.002			−0.022			0.008		
	(0.029)			(0.043)			(0.030)		
rv	0.368			1.299*			0.141		
	(0.287)			(0.725)			(0.362)		
bond		−0.007			−0.012			−0.001	
		(0.009)			(0.014)			(0.015)	
fx		0.007			0.003			0.011	
		(0.006)			(0.008)			(0.008)	
com		−0.011			−0.013			−0.011	
		(0.010)			(0.017)			(0.011)	
ir		0.006			0.019			0.0003	
		(0.006)			(0.016)			(0.003)	
stk		−0.001			0.001			−0.002	
		(0.009)			(0.013)			(0.011)	
l-or			−0.106**			−0.071			−0.184**
			(0.051)			(0.071)			(0.078)
h-or			0.083			0.129			−0.051
			(0.067)			(0.090)			(0.082)
l-spread			0.005			0.008			0.029
			(0.057)			(0.075)			(0.086)
h-spread			0.039			0.054			−0.007
			(0.045)			(0.056)			(0.076)
l-amihud			−14.389			−23.040**			19.707
			(10.699)			(11.650)			(21.746)
h-amihud			17.337*			21.814*			5.200
			(10.344)			(12.665)			(18.575)
Adjusted R^2	-0.0001	-0.009	0.027	-0.002	-0.012	0.033	-0.008	-0.035	0.026

Note: *p<0.1; **p<0.05; ***p<0.01

Table 26: Factor Regression Results for Energy

Returns on Extended Risk Factors by Time Period: vix denotes the implied volatility index, rv denotes realized volatility, bond, fx, com, ir and stock are the trend-following factors of Fung and Hsieh (2001), l-or, h-or, l-spread, h-spread, l-amihud and h-amihud are the commodity factors of Szymanowska, De Roon, Nijman, and van den Goorbergh (2014). l-or (h-or) are the portfolio returns of outright contracts sorted on the basis, l-spread (h-spread) are the portfolio returns of calendar spreads sorted on the basis, l-amihud (h-amihud) are the portfolio returns of outright contracts sorted on the Amihud (2002) illiquidity measure. Newey and West (1987) standard errors in parenthesis.

	Monthly Excess Return (%)								
	1990-2013			1990-2004			2005-2013		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
alpha	0.855	0.574**	0.684***	−1.469	0.232	0.594*	2.618**	1.013***	0.686**
	(0.663)	(0.238)	(0.247)	(0.910)	(0.297)	(0.353)	(1.097)	(0.363)	(0.291)
vix	−0.024			0.139**			−0.108**		
	(0.037)			(0.061)			(0.051)		
rv	0.449			−5.183***			1.561***		
	(0.782)			(1.756)			(0.414)		
bond		0.004			0.010			−0.002	
		(0.013)			(0.016)			(0.021)	
fx		−0.031***			−0.043**			−0.008	
		(0.011)			(0.019)			(0.012)	
com		0.022			0.052*			−0.012	
		(0.018)			(0.029)			(0.015)	
ir		0.001			0.021			−0.007	
		(0.012)			(0.022)			(0.011)	
stk		0.013			0.011			0.014	
		(0.017)			(0.027)			(0.020)	
l-or			−0.041			−0.187			0.077
			(0.108)			(0.147)			(0.133)
h-or			0.198*			0.190			0.055
			(0.105)			(0.126)			(0.122)
l-spread			0.046			−0.049			0.216
			(0.118)			(0.151)			(0.173)
h-spread			0.095			0.056			0.234
			(0.131)			(0.165)			(0.286)
l-amihud			−1.809			−4.506			15.274
			(19.382)			(21.939)			(41.703)
h-amihud			−13.608			8.179			−27.389
			(24.188)			(25.215)			(47.798)
Adjusted R^2	-0.005	0.003	0.0003	0.028	0.025	0.00003	0.035	-0.029	0.037

Note: *p<0.1; **p<0.05; ***p<0.01

Table 27: Factor Regression Results for Meats

Returns on Extended Risk Factors by Time Period: vix denotes the implied volatility index, rv denotes realized volatility, bond, fx, com, ir and stock are the trend-following factors of Fung and Hsieh (2001), l-or, h-or, l-spread, h-spread, l-amihud and h-amihud are the commodity factors of Szymanowska, De Roon, Nijman, and van den Goorbergh (2014). l-or (h-or) are the portfolio returns of outright contracts sorted on the basis, l-spread (h-spread) are the portfolio returns of calendar spreads sorted on the basis, l-amihud (h-amihud) are the portfolio returns of outright contracts sorted on the Amihud (2002) illiquidity measure. Newey and West (1987) standard errors in parenthesis.

	Monthly Excess Return (%)								
	1990-2013			1990-2004			2005-2013		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
alpha	0.484	0.212	0.125	0.787	0.324	0.231	0.486	0.078	−0.098
	(0.527)	(0.200)	(0.158)	(0.609)	(0.263)	(0.209)	(0.710)	(0.279)	(0.279)
vix	−0.013			−0.043			−0.013		
	(0.032)			(0.037)			(0.044)		
rv	−0.010			1.616			−0.148		
	(0.303)			(1.297)			(0.402)		
bond		−0.024**			−0.026*			−0.024**	
		(0.010)			(0.014)			(0.011)	
fx		0.021***			0.022**			0.019	
		(0.008)			(0.010)			(0.014)	
com		−0.004			−0.016			0.007	
		(0.013)			(0.016)			(0.019)	
ir		0.004			0.006			0.003	
		(0.006)			(0.008)			(0.006)	
stk		−0.007			−0.006			−0.007	
		(0.011)			(0.016)			(0.012)	
l-or			0.103			0.137			0.074
			(0.063)			(0.091)			(0.095)
h-or			0.109			0.112			0.154
			(0.080)			(0.093)			(0.139)
l-spread			0.141**			0.148*			0.142
			(0.067)			(0.084)			(0.151)
h-spread			0.103**			0.081			0.230***
			(0.051)			(0.063)			(0.077)
l-amihud			9.146			8.016			2.268
			(9.254)			(11.992)			(16.134)
h-amihud			−17.519			−24.220			−10.920
			(13.086)			(16.197)			(28.081)
Adjusted R^2	-0.005	0.020	0.046	0.001	0.018	0.012	-0.010	-0.014	0.081

Note: *p<0.1; **p<0.05; ***p<0.01

Table 28: Factor Regression Results for Metals

Returns on Extended Risk Factors by Time Period: vix denotes the implied volatility index, rv denotes realized volatility, bond, fx, com, ir and stock are the trend-following factors of Fung and Hsieh (2001), l-or, h-or, l-spread, h-spread, l-amihud and h-amihud are the commodity factors of Szymanowska, De Roon, Nijman, and van den Goorbergh (2014). l-or (h-or) are the portfolio returns of outright contracts sorted on the basis, l-spread (h-spread) are the portfolio returns of calendar spreads sorted on the basis, l-amihud (h-amihud) are the portfolio returns of outright contracts sorted on the Amihud (2002) illiquidity measure. Newey and West (1987) standard errors in parenthesis.

	Monthly Excess Return (%)								
	1990-2013			1990-2004			2005-2013		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
alpha	0.426**	0.129**	0.134**	0.344	0.077	0.128	0.506**	0.177***	0.195***
	(0.179)	(0.054)	(0.065)	(0.264)	(0.083)	(0.102)	(0.217)	(0.054)	(0.070)
vix	−0.019**			−0.017			−0.018*		
	(0.010)			(0.016)			(0.010)		
rv	0.233**			0.167			0.204**		
	(0.109)			(0.381)			(0.095)		
bond		−0.0005			0.004			−0.007	
		(0.003)			(0.005)			(0.005)	
fx		−0.003			−0.006			0.003	
		(0.003)			(0.004)			(0.005)	
com		0.004			0.006			0.003	
		(0.004)			(0.007)			(0.003)	
ir		0.003*			0.007*			0.001	
		(0.002)			(0.004)			(0.002)	
stk		−0.001			−0.001			−0.001	
		(0.003)			(0.004)			(0.004)	
l-or			0.016			0.009			0.006
			(0.024)			(0.035)			(0.020)
h-or			0.080**			0.107**			0.017
			(0.032)			(0.050)			(0.025)
l-spread			0.016			0.020			−0.019
			(0.026)			(0.034)			(0.047)
h-spread			0.017			0.024			0.017
			(0.017)			(0.022)			(0.035)
l-amihud			−3.395			−4.799			3.611
			(4.023)			(5.094)			(5.393)
h-amihud			−5.638			−5.131			−5.397
			(4.627)			(6.699)			(5.020)
Adjusted R^2	0.004	-0.007	0.014	-0.005	0.001	0.024	0.007	-0.019	-0.049

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 29: Down- and Upside Factor Regression Results for the Portfolio

Returns on Common Risk Factors by Time Period: mkt, smb, hml and umd denote the market, size, value and momentum factor for equities from Kenneth French's website (Fama and French (1992) and Jegadeesh and Titman (1993)), liq denotes the Pastor and Stambaugh (2003) liquidity factor, val, mom and tsmom denote the commodity value, commodity momentum and commodity time series momentum factors of Asness, Moskowitz, and Pedersen (2013) and Moskowitz, Ooi, and Pedersen (2012). "+" and "−" denote the upside and downside versions of a factor as outlined in Section 5.1.2. Newey and West (1987) standard errors in parenthesis.

	Monthly Excess Return (%)		
	1990-2013	1990-2004	2005-2013
	(1)	(2)	(3)
alpha	0.261***	0.131	0.477***
	(0.100)	(0.117)	(0.169)
mkt^{+}	−0.015	−0.022	−0.007
	(0.026)	(0.033)	(0.046)
mkt^{-}	−0.024	−0.023	−0.017
	(0.031)	(0.046)	(0.039)
mkt^{-}	0.016	0.024	−0.039
	(0.031)	(0.037)	(0.075)
smb^{+}	0.028	0.027	−0.035
	(0.039)	(0.043)	(0.108)
smb^{-}	0.009	0.015	0.017
	(0.029)	(0.039)	(0.050)
hml^{+}	−0.056	−0.088*	0.007
	(0.040)	(0.053)	(0.080)
hml^{-}	−0.003	−0.011	0.022
	(0.021)	(0.029)	(0.034)
umd^{+}	−0.016	0.010	−0.042**
	(0.019)	(0.022)	(0.018)
Adjusted R^2	-0.012	-0.016	-0.045
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 30: Down- and Upside Factor Regression Results for the Portfolio

Returns on Common Risk Factors by Time Period: mkt, smb, hml and umd denote the market, size, value and momentum factor for equities from Kenneth French's website (Fama and French (1992) and Jegadeesh and Titman (1993)). "+" and "−" denote the upside and downside versions of a factor as outlined in Section 5.1.2. Newey and West (1987) standard errors in parentheses.

	Monthly Excess Return		
	1990-2013	1990-2004	2005-2013
	(1)	(2)	(3)
alpha	0.110	−0.117	0.456***
	(0.100)	(0.121)	(0.149)
val^{+}	0.015	0.028	−0.005
	(0.018)	(0.022)	(0.032)
val^{-}	−0.009	−0.0003	−0.018
	(0.025)	(0.035)	(0.033)
val^{-}	0.047**	0.044	0.052
	(0.022)	(0.028)	(0.038)
mom^{+}	−0.020	−0.007	−0.045
	(0.034)	(0.042)	(0.042)
mom^{-}	0.031	0.055	0.016
	(0.030)	(0.045)	(0.036)
$tsmom^{+}$	−0.035	−0.055	−0.011
	(0.029)	(0.071)	(0.024)
Adjusted R^2	0.034	0.040	-0.006

Note: *p<0.1; **p<0.05; ***p<0.01

Table 31: Down- and Upside Factor Regression Results for the Portfolio

Returns on Common Risk Factors by Time Period: bond, fx, com, ir, stock are the trend-following factors of Fung and Hsieh (2001). "+" and "−" denote the upside and downside versions of a factor as outlined in Section 5.1.2. Newey and West (1987) standard errors in parenthesis.

	1990-2013	1990-2004	2005-2013
	(1)	(2)	(3)
alpha	0.305***	0.165	0.499***
	(0.087)	(0.130)	(0.146)
$bond^+$	−0.008	−0.004	−0.011
	(0.006)	(0.009)	(0.009)
$bond^-$	−0.006	0.007	−0.028
	(0.015)	(0.020)	(0.020)
com^+	−0.002	−0.001	0.003
	(0.005)	(0.011)	(0.006)
com^-	−0.007	−0.016	−0.003
	(0.014)	(0.020)	(0.019)
ir^+	0.008	0.005	0.006
	(0.007)	(0.013)	(0.006)
ir^-	−0.012	0.006	−0.013
	(0.016)	(0.031)	(0.017)
fx^+	0.003	0.015*	−0.003
	(0.005)	(0.008)	(0.003)
fx^-	0.002	−0.060***	0.022**
	(0.012)	(0.019)	(0.010)
stk^+	0.002	−0.003	0.008
	(0.007)	(0.011)	(0.008)
stk^-	0.007	0.015	0.005
	(0.009)	(0.015)	(0.013)
Adjusted R^2	-0.018	0.011	-0.011
Note:			*p<0.1; **p<0.05; ***p<0.01

Table 32: Down- and Upside Factor Regression Results for the Portfolio

Returns on Common Risk Factors by Time Period: l-or, h-or, l-spread, h-spread, l-amihud, h-amihud are the commodity factors of Szymanowska, De Roon, Nijman, and van den Goorbergh (2014). l-or (h-or) are the portfolio returns of outright contracts sorted on the basis, l-spread (h-spread) are the portfolio returns of calendar spreads sorted on the basis, l-amihud (h-amihud) are the portfolio returns of outright contracts sorted on the Amihud (2002) illiquidity measure. "+" and "−" denote the upside and downside versions of a factor as outlined in Section 5.1.2. Newey and West (1987) standard errors in parentheses.

	Monthly Excess Return (%)		
	1990-2013	1990-2004	2005-2013
	(1)	(2)	(3)
alpha	0.239***	0.223	0.267**
	(0.088)	(0.142)	(0.135)
l-or$^+$	−0.028	−0.036	−0.040
	(0.035)	(0.046)	(0.047)
l-or$^-$	0.018	−0.080	0.115*
	(0.054)	(0.096)	(0.061)
h-or$^+$	0.094**	0.088*	0.055
	(0.038)	(0.053)	(0.056)
h-or$^-$	0.134***	0.149**	0.011
	(0.049)	(0.071)	(0.053)
l-spread$^+$	0.105**	0.071	0.171**
	(0.051)	(0.057)	(0.067)
l-spread$^-$	−0.012	−0.024	−0.088
	(0.033)	(0.036)	(0.094)
h-spread$^+$	0.116**	0.098	0.165**
	(0.049)	(0.065)	(0.070)
l-spread$^-$	−0.025	−0.021	−0.118***
	(0.039)	(0.050)	(0.041)
l-amihud$^+$	−0.260	−4.842	6.211
	(7.133)	(8.830)	(11.853)
l-amihud$^-$	4.912	7.540	19.062*
	(8.742)	(10.668)	(10.011)
h-amihud$^+$	−3.424	−1.062	−6.333
	(6.423)	(7.573)	(12.574)
h-amihud$^-$	−20.260**	−10.791	−26.159**
	(9.321)	(10.759)	(12.605)
Adjusted R^2	0.105	0.076	0.157
Note:			*p<0.1; **p<0.05; ***p<0.01

C.1 Seasonality

Contrary to the equity markets, in which seasonality is often believed to be a data mining artifact, commodity futures markets may display seasonal behavior as the information flow relating to the spot price is different throughout the year. In agricultural products, the harvest months provide a natural reason to expect different price behavior in these months. For energy contracts, we can also expect to see different behavior during the heating season than during the rest of the year. While it is clear from the above intuition and also well documented in the literature, e.g. Fama and French (1987), that the spot price and the outright futures prices display seasonal patterns in the commodity markets, it is not obvious that calendar spreads do so also. We therefore test for seasonality as in Fama and French (1987), by running the following regression

$$R_{m,t} = \beta_0 + \sum_{i=1}^{11} \beta_i d_i + \varepsilon_t, \tag{10}$$

where the d_i's are monthly dummies and $R_{m,t}$ are the monthly returns to the strategy. The results are shown in Table 33. Overall, we find very limited evidence of seasonality in particular for the agricultural commodities.

Table 33: Test for Seasonality in the Returns
Regression results for monthly excess returns on monthly dummies.

	Monthly Excess Return						
	Grains	Softs	Energy	Meats	Metals	Portfolio	Control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
β_0	0.003	0.002	-0.003	-0.001	-0.002^{*}	-0.0001	0.004
	(0.003)	(0.003)	(0.008)	(0.004)	(0.001)	(0.002)	(0.003)
$I(Month = 1)$	0.001	0.001	0.018	0.002	0.005^{**}	0.005	-0.001
	(0.006)	(0.005)	(0.014)	(0.005)	(0.002)	(0.005)	(0.003)
$I(Month = 2)$	-0.0002	0.007	0.007	0.011^{*}	0.003	0.005^{*}	-0.004
	(0.006)	(0.005)	(0.010)	(0.006)	(0.002)	(0.003)	(0.004)
$I(Month = 3)$	-0.0003	0.012^{**}	0.013	-0.0004	0.0004	0.005	-0.001
	(0.005)	(0.005)	(0.009)	(0.006)	(0.002)	(0.003)	(0.004)
$I(Month = 4)$	-0.003	0.006	-0.004	0.002	0.004^{*}	0.001	-0.001
	(0.006)	(0.005)	(0.009)	(0.005)	(0.002)	(0.003)	(0.004)
$I(Month = 5)$	0.001	-0.004	0.015	0.002	0.004	0.003	-0.011^{***}
	(0.006)	(0.006)	(0.010)	(0.006)	(0.003)	(0.004)	(0.004)
$I(Month = 6)$	0.004	-0.004	0.010	0.004	0.002	0.003	-0.006
	(0.007)	(0.007)	(0.011)	(0.006)	(0.002)	(0.003)	(0.004)
$I(Month = 7)$	-0.005	-0.003	0.019	0.002	0.004^{**}	0.003	-0.011^{***}
	(0.006)	(0.005)	(0.012)	(0.007)	(0.002)	(0.004)	(0.004)
$I(Month = 8)$	0.010^{**}	0.00005	0.008	0.002	0.004^{*}	0.005	-0.009^{**}
	(0.005)	(0.005)	(0.010)	(0.006)	(0.002)	(0.003)	(0.005)
$I(Month = 9)$	0.003	0.001	-0.008	0.009	0.004	0.001	-0.005
	(0.006)	(0.005)	(0.010)	(0.007)	(0.003)	(0.003)	(0.004)
$I(Month = 10)$	-0.001	0.007	0.013	0.010^{*}	0.008^{***}	0.007^{**}	-0.002
	(0.005)	(0.004)	(0.011)	(0.006)	(0.003)	(0.003)	(0.004)
$I(Month = 11)$	-0.004	-0.001	0.010	-0.003	0.005^{**}	0.001	-0.005
	(0.004)	(0.003)	(0.012)	(0.006)	(0.002)	(0.004)	(0.005)
Adjusted R^2	-0.008	0.017	0.014	-0.005	0.017	-0.004	0.022
Note:							$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$