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Strategies for Spread Trading using Futures Contracts

Bachelor thesis

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Anotace (abstrakt)

Tato práce se zaměřuje na spready na futuritních trzích, konkrétně studuje obchodní strategie založené na dvou přístupech - kointegrace otestovaná na inter-komoditních spreadech a sezónnost kterou pozorujeme na kalendářních (intra-komoditních) spreadech. Na párech kontraktů, které jsou kointegrované budeme testovat strategie založené na návratu k průměru. Tři strategie budou využívat filtr tzv. 'férové hodnoty', jedna bude pracovat s hodnotou relativní. Podobným způsobem budeme na kalendářních spreadech testovat strategie typu "buy and hold". Všechny strategie testujeme na in-sample a out-of-sample datech. Sezónní strategie nevygenerovaly dostatečně ziskové strategie, některé inter-komoditní spready se naopak ukázaly jako profitabilní v obou testovacích periodách. Výjimku u inter-komoditních spreadů tvořily zejména všeobecně známé spready, které v out-of-sample testech neobstály.

Klíčová slova

Futuritní kontrakty, kointegrace, sezónnost, strategie založené na reverzi k průměru, futuritní spready

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Abstract

The focus of this thesis are futures spreads, more specifically trading strategies based on two approaches - cointegration tested on inter-commodity spreads and seasonality observed amongst calendar spreads. Commodity pairs which we identify to be cointegrated are tested for four mean reversion strategies, three of them being based on fair value approach, the fourth on the relative value approach. Similarly calendar spreads exhibiting seasonality are optimized for naive buy and hold trading strategies. Both approaches are tested on in-sample and out-of-sample data. Amongst seasonal strategies we have not found a pattern yielding sufficiently profitable signals in both in-sample and out-of-sample periods. Inter-commodity spreads on the other returned profitable strategies on cointegrated spreads which were also similar in physical nature. The exception to that rule were spreads known well in the industry, which failed to deliver positive results in the out-of-sample period.

Keywords

Futures contracts, cointegration, seasonality, mean-reverting trading strategies, futures spreads

JEL classification: G13, G14, G17

Declaration of Authorship

I hereby proclaim that I wrote my bachelor thesis on my own under the leadership of my supervisor and that the references include all resources and literature I have used.

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Prague, 18 May 2017

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Acknowledgment

I would like to express my gratitude to my thesis supervisor doc. PhDr. Ladislav Krištoufek Ph.D. for his advice and guidance, as well as for the Data Science with R class, without which this thesis would not exist.

Bachelor Thesis Proposal

Author	Oskar Gottlieb
Supervisor	doc. PhDr. Ladislav Krištoufek Ph.D.
Proposed topic	Strategies for spread trading using futures contracts

Preliminary topic characteristics The objective of this thesis is to come up with trading strategies robust enough to yield positive results in the futures markets. Futures spread became an instrument of grande importance, as it systematically mitigates risk, offers lower volatility than the outright contract and creates space for new trading strategies and approaches (such as seasonality). We will be focusing on studying longer term strategies, using the daily charts on some of the major futures exchanges. We will try to cover examples of intracommodity, intercommodity as well intermarket (also called inter-exchange) spreads. The strategies would be created with respect to the tools and conditions that average retail trader has to face (size of commision per round turn, latency, access to data).

The futures spreads will be created using End of the day time series data of various futures contracts, the data will be downloaded from various exchanges through Quandl.com. The data will be downloaded through Quandl's publically available API, using Python and it will be stored in a Postgresql database. Using the time series analysis, we will be looking for trends, patterns and general similarities in behaviour accross thousands of spread combinations. This paper should present basic methods and ideas applicable in the futures markets. It should also comment on the longer term trends and possible explanation of the changes futures spread market has gone through in the last few decades.

Outline

1. Introduction - methodology, literature review
2. Data manipulation
3. Creation of the models
4. Analysis of models and their optimization
5. Conclusion

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Author

Supervisor

Contents

1 Introduction

Futures markets nowadays form a crucial part of the financial systems. The importance of futures markets has been nicely summarized by Carlton (1984), who states that they bring a form of certainty to businesses who rely on the physical delivery of various commodities. Those willing to reduce their exposure to the market (hedgers), transform the risk to those who are willing to take it (speculators). He also points out that although futures markets play a similar role as forward markets, futures outperform them in terms of transaction costs. Both forward and futures contracts enable any market participant to hedge themselves against adverse market movements. Yet the two types of contracts are different in terms of market organization - forwards are highly customized contracts, traded over the counter. In contrast, futures are highly standardized and centralized, therefore they exhibit higher volumes and allow for lower transaction costs. Higher liquidity then enables using slightly more complex strategies, such as spreading a position. In general terms, a spread means simultaneous purchase and sale of two assets with the expectation that the difference in their prices will either increase (in the case of being long - buying the spread) or decrease (in the case of being short - selling the spread). This is applicable not only to futures contracts but also to other instruments, such as stocks and to certain degree to forwards too. Futures contracts thanks to their standardization provide a reliable, repetitive structure on top of which we can better build our strategies.

There are three main types of futures spreads, intra-market (also called calendar spreads), inter-market and inter-exchange. Intra-market spreads are traded on one exchange, in one contract with different delivery months. Inter-market are again traded on the same exchange, although multiple contracts can be used. An example of such trade would be buying silver and selling gold futures, both contracts being quoted on Chicago Mercantile Exchange (CME). The last type of spread has legs on multiple exchanges and usually, the respective contracts are different as well. Futures spreads became a popular instrument for both hedgers and speculators. Hedgers can lock-in abnormal profits as documented by Kenyon and Clay (1987) and speculators make use of lower margin on spreads (when compared to outright positions).

In this thesis I will be looking into potential discrepancies and abnormalities in multiple inter-commodity spreads, including the ones which are important enough to have their own name e.g. crush spread, spark spread or the crack spread. Based upon the abnormalities we will be forming various trading strategies which will be tested on both in-sample and out-of-sample data. This bachelor thesis has the following structure: Chapter 2 summarizes main academic literature concerning futures spreads. It looks into spread trading of both inter-commodity and calendar spreads. Next it goes through the theoretical models that we will be applying. Three main types of methods will be studied, seasonality, mean-reverting and trend following approach. Chapter 3 describes the data used and their transformation, including a brief description of the inter-commodity spreads. Chapter 4 provides general theory of the econometric models and the introduction of trading strategies. Chapter 5 will summarize results of the co-integration approach and of the used mean-reverting strategies on both in-sample and out-of-sample data. Chapter 6 then presents the results of seasonality approach. Finally, Chapter 7 concludes our findings.

2 Literature Review

The economic importance of spreading futures contracts has been studied throughout the years and it has been approached variously. To mention a few of these approaches, Daigler (2007) wrote about the important contribution of spreads to the total volume in the currency market, Kenyon and Clay (1987), Leuthold and Mokler (1979) looked at ways to decrease the variance of company's profits in the hogs and cattle industry, respectively.

One of the first academic papers published on the subject of futures spread is a paper by Working (1949). Working found empirically, that the main reason for price differentials between individual futures contracts is the cost of carry depending on current stock of the respective commodity, rather than the difference in expectations of the supply and demand of the two contracts. The relationship between two futures contracts, in this case, could be represented with this simple formula:

$$F_0^{t_1} = F_0^{t_2} + c_t \tag{1}$$

$F_0^{t_1}$ and $F_0^{t_2}$ are the current prices of the futures contracts expiring at times t_1 and t_2 respectively, where $t_1 < t_2$. Cost of carry (represented by c_t) includes all the costs necessary for carrying the underlying commodity (or any other asset for that matter) from one expiration date to the other. Arbitrage opportunities are present if the price deviates substantially from the mentioned relationship.

As we already know, we can divide spreads into three main categories, all of which will be studied in this thesis. Inter-exchange and inter-commodity will be traded in similar manner, intra-commodity spreads are adepts for seasonal strategies. Calendar futures spreads (intra-commodity) are generally regarded as lower risk instruments, mainly when compared with outright positions, Tucker (2000). This idea is based on the high long-run correlation between the legs of a spread, exogenous shocks then affect both legs of the spread, making it less risky by definition. Kawaller et al. (2002) compare the risk and returns of calendar spreads and outright positions. They argue that spreads should not be regarded as substitute of outright positions, rather given the low correlation between them and outright positions, the calendar spreads can be used for portfolio diversification. Next, under assumption of normal distribution of returns of both outright positions and calendar spreads, they constructed the Value-at-Risk model, adjusting the number of contracts used in spread to achieve same average return mean as in the outright counterpart. They found that in order to achieve the same mean return, volatility of the spreads is greater than that of the outright positions.

Dutt et al. (1997) divide calendar spreads into two more categories: intra-crop (contracts expire during one crop) and inter-crop (contracts expire during different crops). Their analysis of various agricultural commodities from July 1983 until August 1991 concludes that even though both intra-crop and inter-crop spreads are highly correlated, the hypothesis that the correlation of the two types equals, is rejected. The legs of the inter-crop spread are less correlated with one another and also more volatile than the second type, which is a direct consequence of Working's theory of storage.

Mean-reverting spread trading strategies have been quite extensively studied in the last few decades, mainly on inter-commodity spreads, which have an economic significance. Rechner and Poitras (1993) studied the soybean crush spread behavior, they created intra-day strategies based on the gross processing margin (GPM) which copies the physical relationship and its output gives the margin in per bushel units. Authors place trades and hold them only through one day, their "naive" strategy buys the spread if the open price is less than previous day's close and sells the spread if the opposite is true. In order to limit the number of trades, filters based on the deviation from GPM are employed. Strategies with 1-cent, 2-cent or 3-cent filter turned out as profitable over the years 1978 - 1991, it also held true that higher value of the cent filter leads to higher mean profit per trade as well as fewer trades.

Simon (1999) first tests the behavior of the soybean spread for mean-reverting toward the 5-day moving average under a GARCH (Generalized AutoRegressive Conditional Heteroskedasticity) process, as it can deal with time-varying volatility of the crush spread. Only then does he form strategies, where the position is opened based on the deviations of X of the spread from its long-run equilibrium (also referred to as fair value) and/or Y from its 5-day moving average. The trade is reversed (closed) only if the spread is X above (below) its moving average in case of long (short) position. Most of Simon's strategies in the 1985-1995 period yielded positive results (commissions were included), similar conclusion was reached that the number of trades decreases in number and increases in mean profit, as the size of the filter figures X and Y increases.

Mitchell (2010) revisits the crush spread a decade later, although his research paper is based on Simon (1999) there are a couple of differences between the two. For instance Mitchell argues that even if Simon found mean-reversion, this does not necessarily imply that the spread will keep trading around its equilibrium and any larger deviations in the adverse direction could significantly impact the bottom line. He also introduces truncating trades (closing trades based solely on the duration of the position), as according to his results winning trades are held on average for shorter periods than losing trades are. Contrary to Simon, Mitchell failed to find strategies which would be significantly profitable, even after employing more advanced techniques such as the already mentioned truncating. He, therefore, concluded that "the soybean crush spread should be considered an efficient market".

Liu and Sono (2016) contrary to previous papers study the crush spread on China's Dalian Commodity Exchange (DCE). Their motivation is also driven by the fact that China became the largest soybeans importer in 2009. Similarly to Simon (1999), authors employ a model which is similar to the

Engle and Granger (1987) co-integration model. After rejecting the null hypothesis of no cointegration relations, mean-reverting trading strategies are introduced. To be exact, two strategies are introduced and again Simon's paper served as the main inspiration. In the first strategy, the trade is initiated after the distance from the fair value of the crushing margin is larger than a multiple of X of standard deviation. The second one is triggered if the position deviates from the moving average by Y. Both strategies, in the end, yield positive results.

Similarly, other products have been studied as well Emery and Liu (2001) analyze the spark spread, that is spread between electricity and natural gas futures. After testing for cointegrated relation, the authors found profitable strategies for both Palo Verde and California-Oregon electricity contracts. Their analysis is divided into two samples, one used for in-sample testing, one as out-of-sample. Their strategy (similar to the ones already mentioned, based on multiples of the standard deviation from its long-run equilibrium) turned out as profitable in both periods. Wahab et al. (1994) study the efficiency of gold-silver spread by looking for potential arbitrage opportunities between the two commodities. Their error correction model does find some profit, however that is before the transaction costs (commissions) are accounted for. Moving average based strategy in this model yields negative results, even before we subtract commissions. Liu (2005) also studied the hog spread (hog, corn and soybean contracts), finding profitable strategies for both ex-post and ex-ante simulations. The strategy being the same as the ones we have already covered. Commodities were not the only assets studied, Butterworth and Holmes (2002) were investigating the inter-market spread between the UK stock indices FTSE 100 and Mid 250. According to their findings, the two markets usually trade within their transaction costs (commissions and slippage) boundaries and any potential profit is dismantled by these costs which appear once we would want to flat the position.

Out of the main spreads, the most popular one in academic literature seems to be the crack spread or other spreads, which include crude oil and its products. Dunis et al. (2006a) based their research on the paper by Butterworth and Holmes (2002), extending it by testing 4 different approaches on the WTI - Brent (both crude oil contracts) spread, both in-sample and out-of-sample. These approaches are namely the fair-value approach, deviation from moving averages, time series forecasting based on GARCH(4,2), ARMA(8,8)[1] and model and finally neural network regression. For each of these strategies, standard and correlation filters were applied the former being the one we already covered in fair-value approach. The latter is introduced with the idea of filtering periods of little to no spread movement (that is the correlation is increasing) and only looking at periods of spread divergence (when the correlation is decreasing). The vast majority of their strategies turned profitable (the exception is the GARCH model) both in-sample and out-of-sample. The correlation filter has underperformed the standard one and out of all the various strategies, ARMA and MACD models came out as winners, MACD even had better performance in one out-of-sample than in the in-sample period. Very similar paper again by Dunis et al. (2006b) in the crack spread (WTI crude oil against NYMEX Unleaded gasoline) employed strategies more focused on neural networks. Both recurrent neural network and higher order neural networks outperformed the fair-value model, that is however before transactions are accounted for. Due to the higher number of trades and relatively high commission costs, the neural networks under various filters were not performing as well. Dunis et al. (2010) came to the oil based spreads a few years later, using very similar methods found again inefficiencies which could be exploited. This time the neural network regression outperformed all the other models in terms of both in-sample and out-of-sample performance. Next, Westgaard et al. (2011) studied the co-integration of ICE Brent and gas oil contracts

[1] The authors present it as ARMA(1245678, 12367) model, as it's a ARMA(8,8) model short of 3rd auto regressive term and of the 4th,5th and 8th moving average terms.

at various time length to maturity. They found evidence in the 1994-2009 but period of 2002-2009 on its own did not have enough evidence to reject the null hypothesis of no co-integration. They attribute this to the volatile period of both the financial crisis and the hurricane Katrina. Finally Lubnau and Todorova (2015) formed calendar spreads from WTI, gasoline, heating oil and natural gas contracts. Their strategy was again based on deviation from the mean, they used Bollinger bands (a technical indicator based on moving average) to enter trades and exited once the price was at the value of its moving average again. Let's now look at the second major way the future spreads are traded.

Seasonality in the asset markets is not strictly the domain of futures contracts. In 1964 the magazine Financial times mentioned in an article the now famous financial adage Sell in May and go away [2].This proverb was based on rather anecdotal evidence of stock market returns being higher in the first half of a year than in the rest of the year. It was later investigated by Bouman and Jacobsen (2002), who found statistically significant higher returns in January across stock markets. This was in direct contradiction with the weaker form of efficient market hypothesis (EMH) (Fama, 1970). Dichtl and Drobetz (2015) later failed to find statistical evidence of Sell in May and go away in the period following Bouman and Jacobsen's paper. Their explanation was that as the original anomaly became easily accessible, it was also easily exploitable, markets therefore corrected their mispricing in the years following the publishing.

Another example of seasonality in the stock market is the so-called January effect, according to which markets perform abnormally better during January than during other months. Gultekin and Gultekin (1983) found that January effect was significant in 15 out of 17 countries that have been studied.Similarly Haugen and Jorion (1996) found evidence of January effect

[2]The excerpt from Bouman and Jacobsen (2002): "The Stock Exchange world is in a sort of twilight state at the moment. The potential buyers seem to have "Sold in May and gone away"

in the S&P 500 index, they however also add that due to transaction costs, this discrepancy might not be automatically turned into a profitable trading strategy.

Although stock and commodity (futures) markets differ in terms of general structure, January effect has also been found in the futures markets as documented by Gay and Kim (1987). Their analysis of the Commodity Research Bureau (CRB) Index yielded a significant result in the 1956-1981 period. They however also add, that this effect ceased to exist in 1981 when Congress passed the Economic Recovery Act. The taxing of futures contracts has changed, marking losses with 60% to 40% ratio of them being treated as long-term and short-term losses, respectively. Also, positions at the end of the year were treated as marked-to-market, making any tax optimization techniques practically obsolete. The following period of 1982-1985 failed to show the significance of January effect.

Seasonality has been further studied mainly in agricultural and electricity-related commodities. Vaughn et al. (1981) identified statistically significant seasonal effects in futures contracts such as live cattle, wheat or soybeans. As the authors point out, their findings, however have to be approached more "generally" and a strategy can not be based simply on the market tendencies. Malick and Ward (1987) found seasonality in the basis of frozen concentrated orange juice (FCOJ) futures as a function of its stocks. The already mentioned Emery and Liu (2001) have identified seasonality in the price of electricity. This behavior has been caused most likely by the increased demand for air conditioning in the summer months. Similarly Geman (2012) finds mild seasonality in cocoa, yet he does not go as far to form any trading rules around it.

Based on seasonality existing in commodities we can build more complex structures, such as spreads - both intra and inter-commodity have been studied in the past. Girma and Paulson (1998) studies seasonality in different variations of the crack spread, he initiates the position once the spread is at its seasonal peak (trough) and then the authors tested various holding periods. Spreads turn out to be mainly profitable with the 10 and 12 weeks long holding periods in both the in-sample and out-of-sample period. However only the results of the 'main' 3-2-1 crack spread remain significant in both testing periods. Cole et al. (1999) look globally at all major crush and crack spreads, they found strongest seasonality to be present in the oil-based spreads, not as strong seasonality in soybean crush spreads and only mild one in the cattle spread. Their strategy was again a simple set of buy and hold rules, where they bought (sold) the given spread when it was at its seasonal low (high), held the trade and sold (bought) it back again when it was at its high (low). The authors distinguish between so-called incremental, expected and deferred spreads. Incremental spreads suppose from purely theoretical standpoint the immediate delivery, processing, sale and shipment of the original commodity. Therefore the contracts have the same or as close delivery dates as possible. On the other hand, expected spreads are more realistic, as there is a time difference between the time raw material is delivered and the time products of this material are sold and delivered to another business or consumer. Last category, differed spreads, are expected spreads missing the rolling from one set of contracts to another. Contrary to the results of spread's seasonality, crack spread strategies incurred losses in any form, whereas deferred May and incremental cattle crush spreads have been profitable.

Barrett and Kolb (1995) test various spreads consisting of corn, wheat and soybeans contracts. The spreads which were picked came from a booklet provided by Chicago Board of Trade (formerly CBOT, now CME) and the authors approached them with caution, as they were presented in a non-academic way with no additional statistic of any sort. They failed to find any significant regularities which could be exploited systematically and therefore they did not even go as far as forming any trading rules around these spreads. Abken (1989) studied the inter-market spreads in heating oil. Their approach is quite simplistic in nature, they constructed multiple time series for each combination of a deferred (farther away) contract and a sooner expiring contract. At the end of every month they roll their current position into a position with the same month differential between the two legs, making use of the fact that heating oil expires every single month and is therefore very regular in nature. After dividing their time series into two samples - winter (November - April) and summer (May - October) they run their simple strategy which is based on the general backwardation of the spread, selling the spread at the beginning of each month and rolling the position as mentioned. In the summer period, all contract months combinations were statistically insignificant with not even one spread being below 10% p-value. In the winter period on the other hand multiple spreads had significantly positive results (even after accounting for commissions), but only those which had the sooner expiring leg only one to two months away from the expiration.

Similarly to the 'strategies' published by CBOT, there have been also non-academic publications such as Bernstein (1990) who wrote about various calendar spreads but without any significant amount of quantitative or academic research. Salcedo (2004) also lists a number of spreads with their basic metrics such as the number of winning and losing days and their average size in recent years. He, however, fails to mention other important information such as the variance of these trades, Sharpe ratio or any econometric model that might be driving this behavior. It will be therefore interesting to see in our analysis whether these spreads managed to keep their profitability even years after they have been published.

3 Data

3.1 The dataset

The list of used commodities can be seen in Table 1. With the exception of RBOB Gasoline and TF E-mini Russel contracts, we will be using data from January 2000 until December 2016. RBOB started trading in 2006 and TF's dataset prior to 2002 is corrupted. Also two silver contracts had to be abandoned due to data corruption - SIM03 and SIX11, Silver futures of June 2003 and November 2011, respectively. The data will be divided into in-sample and out-of-sample parts, one more calibration part will be added for the neural network regression. TF's, periods as well as RBOB's, will be shortened and adjusted accordingly. We will use contracts which are listed on Chicago Mercantile Exchange (CME), New York Mercantile Exchange (NYMEX) and Intercontinental Exchange (ICE). All data has been gathered through public databases[3][4] on the Quandl.com website. For each contract, we will be using the 'settle' price, which represents the settlement price at the end of the day (EOD).

The problem with futures contracts is that they expire periodically and therefore the data for each contract has a short time span. In order to create continuous contracts, we will need to 'roll-over' the position from one month to the other. Rolling forward is a process of closing the soon-to-expire contract and opening the same position in a different contract. In literature, a couple of rules are applied. Simon (1999) rolls over on the first day of the month which precedes the expiration month. Butterworth and Holmes (2002) use contracts closest to the expiration and rolls them over at the day of expiration. Finally Adrangi et al. (2006) abandon the most actively traded contract for the one which expires next on the first day of the expiration month. We will be using approach similar to this one

[3] 'Intercontinental Exchange Futures Data': https://www.quandl.com/data/ICE
[4] 'Chicago Mercantile Exchange Futures Data': https://www.quandl.com/data/CME

with calendar spreads. Instead of rolling on the first day of the expiration month we will be rolling on the last day of the month before the expiration month. It seems to best serve our purpose as we will be looking primarily at commodities, which tend to get more volatile as the expiration approaches. Trading these contracts on the last possible day runs into risk of not being able to liquidate the position. This is something we need to avoid, as a direct consequence of not being flat after expiration date is an obligation to deliver the underlying commodity or to have it delivered. On the other hand, we do not want to roll the position too soon, as we might run into the other extreme of lack of volume and therefore lack of liquidity.

3.2 Notable spreads

Some spreads became so widely traded and economically important that they got their own name in the trading industry. These spreads are generally of commodities which are used in a manufacturing or processing operation.

3.2.1 Crush spread

The crush spread got its name from the process of crushing soybeans into soybean meal, out of which soybean oil is extracted. The United States Department of Agriculture report by Lovell (1988) uses the relationship[5], where on average one bushel (equivalent of 60 pounds) is used to produce 48 pounds (80%) of soybean meal, 11 pounds of soybean oil (18.3%) and 1 pound of waste. As Simon (1999) noted, there are two main types of the crush spread, the poor man's way and the "correct", more precise way. Given the contract specification the more precise way of trading this spread is to buy (sell) 10 soybean contracts, sell (buy) 12 meal contract and sell (buy) 8 oil contracts if we are buying (selling) the spread. As we are not

[5]The relationship remained constant over time, it has been used lately in a report by CME: https://www.cmegroup.com/trading/agricultural/files/pm374-cbot-soybeans-vs-dce-soybean-meal-and-soybean-oil.pdf

interested in hedging ourselves as precisely as possible, we will be mainly looking at the alternative ratio of 1-1-1, which is sufficient for purely speculative purposes. Last characteristic worth mentioning is the discrepancy in contract distribution at the end of the year. The three contracts all expire in January, March, May, July, August and September, however oil and meal then expire in both October and December, whereas soybeans only do in November. Therefore on the first trading day in September, the September contract is dropped and we will use November contract for soybeans and December contract for the other two commodities, bypassing the October contract altogether. Then at the last trading day of October, January contract is picked up. To be more specific Table 2 displays the contracts used with their respective roll over dates.

3.2.2 Crack spread

The name for the crack spread came again from processing crude oil into a range of petroleum products. There are however few types of crack spread, all of which we will be looking into. The default "3-2-1" consists of three long (short) contracts of crude oil, 2 short (long) contracts of unleaded gasoline and 1 short (long) contract of heating oil. Although this spread is more popular, an alternative quotation is "5-3-2". Similarly, the "gasoline crack spread" has a ratio of 1-1-0, long (short) one contract of oil and short (long) contract of unleaded gasoline. Finally "heating oil spread" is characterized by 1-0-1 ratio of one long (short) crude oil contract and one short (long) contract of heating oil. We can use either WTI, LLS or Brent crude oil. Given that all three mentioned contracts expire each and every month, we can simply use the same rule we have applied with calendar spreads. On the last day of the month prior to expiration month, we will switch from one set of contracts to the next in line.

3.2.3 Feeder cattle spread

Next on the list is feeder cattle spread, sometimes called "cattle crush", though it has nothing to do with crushing cattle. Contrary to the two spreads we have mentioned before, feeder cattle spread uses more than one commodity as an input and outputs only one. Buying (selling) this spread implies buying (selling) feeder calves and corn futures and selling (buying) live cattle futures. The most commonly used ratio of contracts is 2-1-1 respectively, although sometimes 10-3-5, 8-2-4 or even 4-1-2 are used, even though they are less precise in their hedging efforts as they over-hedge some commodities and under-hedge other. Problem which arises with raising cattle is that it does not happen overnight. There has to be a time difference in the expiration of the cattle contracts. Usually 4 to 6 months is the rule of thumb, with corn being somewhere around the middle of the two cattle contracts. We will simplify the situation a little bit, table of contracts with their expiration months can be seen in Table 3. The rolls are based on rolls of the feeder cattle contract and other two contracts are picked to fulfil the conditions mentioned above.

3.2.4 Other spreads

Last we will look at all possible spread combinations to see which pairs are cointegrated. Although we could just test for the 'obvious' ones such as spreads of agricultural commodities, or some stock indices, this way we could uncover spreads that we might otherwise miss.

The final spread I would like to mention, which unfortunately we will not be looking into is the spark spread, which consists of selling (buying) electricity futures and buying (selling) the fuel, mainly gas. The reason why we will be skipping this spread is the general unavailability of energy contracts to the retail traders. Other futures can be delivered or can be cash-settled, however it's technically impossible for someone without the proper infrastructure to deliver or have delivered few MWH of electricity. That is why electricity trading is generally restricted only to large energy companies (such as ČEZ).

4 Methodology & Trading Strategies

As I have already mentioned, there are two main methodologies we will be studying. Co-integration analysis on top of which we will be building mean-reversing kind of trading strategies (that is if the legs of given spreads are co-integrated) and seasonality which should produce simple buy and hold trading strategies.

4.1 Cointegration approach

Co-integration is an approach tested quite successfully in the past on various spreads, as documented in the literature review section of this thesis. Given that spread in this sense is constructed from two or more co-integrated outright contracts, its residuals are stationary and from this mean reverting trading opportunities arise. Outright contracts on their own are not by any means stationary and therefore mean-reverting techniques on outrights will not be tested. To illustrate the stationarity property, an analogy with a dog on the leash is usually used. In that case, dog and the dog owner are two objects who move together over time and even though their Euclidean distance varies over time, it tends to revert back to zero, as they are connected via the leash - we would call the distance to be a stationary process. Before looking at co-integration formally, let us first define these terms which we will need.

Let us have a time series:

$$\{y_t\}_{t=1}^{n}, n \in \mathbb{N} \tag{2}$$

Wooldridge (2013) then defines stationary in the following way: A stochastic process is stationary if for every set of time indices $\{t_1, t_2 ... t_n\}$ the joint distribution of $(y_{t_1}, y_{t_2} ... y_{t_n})$ and $(y_{t_{1+h}}, y_{t_{2+h}} ... y_{t_{n+h}})$ is the same for $h \geq 1, h \in \mathbb{N}$

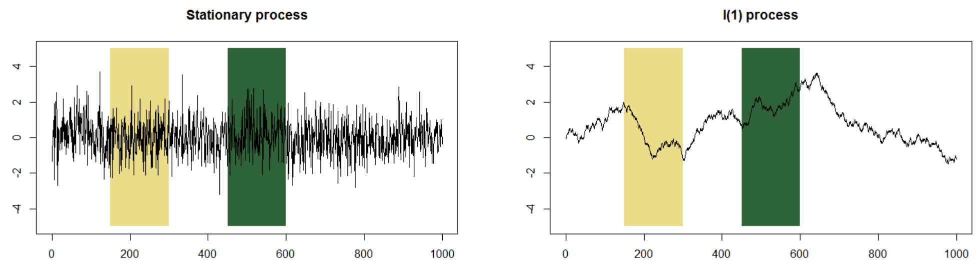

Figure 1: Stationary and non-stationary time series

From the definition, it is not immediately clear what the intuition for stationarity is. We can illustrate it then along with a non-stationary process using two images which can be seen in Figure 1. On the left, the process is a graphical representation of a Gaussian noise and as such is clearly stationary and has strong mean-reverting tendencies. On the right-hand side, we see a representation of a random walk, that is a process which is non-stationary, to be more precise, a random walk is a special case of a unit-root, I(1) process (that is an integrated of order 1).

I(1) processes are a prerequisite for cointegration and luckily when it comes to financial data this condition is frequently satisfied. Empirically we can see and test that price of a stock, commodity or foreign currency has the same tendencies to trend as our right image in Figure 1. Generally a process is integrated of order (d) if it takes us d-times repeated differences of the variable in order to receive a stationary process. Hence I(0) is stationary without the need to do differencing, random walk, on the other hand, can be represented with the equation in (4.1).

$$\begin{aligned} y_t &= \alpha + \beta y_{t-1} + \epsilon_t \\ \epsilon &\in N(0, \sigma^2), \beta = 1 \end{aligned} \tag{3}$$

and will yield a stationary series only after first differencing. In theory such transformation is represented in (4)

$$\begin{aligned}\Delta y_t = y_t - y_{t-1} = \alpha + (\beta - 1) y_{t-1} + \epsilon_t \\ \Delta y_t = \alpha + \theta y_{t-1} + \epsilon_t \\ \theta = \beta - 1 = 0\end{aligned} \tag{4}$$

Again, to illustrate this transformation in practice, let us look at Figure which is in nature similar to Figure 1. We will look at Figure 2, where on the left side we see the chart of the crude oil outright contract and on right-hand side its transformation, same as we have shown theoretically in (4). As we will see later on, crude oil (this and other contract months) are truely I(1) processes.

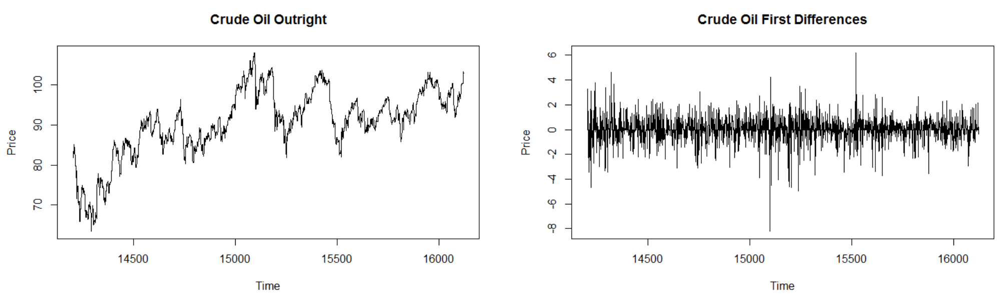

Figure 2: Crude Oil CLH14 contract before and after differentiation.

There are several ways of testing for stationarity, I will shortly present the one Engle and Granger have used, that is a unit root test (quite popular amongst academics) that was first introduced by Dickey and Fuller (1979). Looking again at (4), we now see that it is an equation whose coefficients can be estimated using standard ordinary least squares (OLS) regression. α is the intercept. ϵ_t are independent, identically distributed (i.i.d.) errors, again with mean equal to zero and constant variance σ^2, the coefficient of interest is β or θ if we employ (4) instead. When we want to test for the presence of stationarity, we will set hypothesis in the following way.

$$H_0 : \beta = 1 \iff \theta = 0$$
$$H_1 : \beta < 1 \iff \theta < 0$$

If we fail to reject H_0, we can not reject that the time series has a unit root and the series can be used in further analysis. The case of $\beta > 1$ ($\theta > 0$) is not mentioned here, as that would imply an explosive process - one that can be seen during crashes or boom and bust cycles. However we are interested in behavior of the assets over longer haul and on our time frame, such behavior is highly unlikely to occur.

In practice the augmented version of Dickey Fuller (ADF) test is used more frequently as can be seen in the papers of Simon (1999), Dunis et al. (2010) and Emery and Liu (2001). As the name suggest, ADF is built on top of the standard Dickey-Fuller test, usually the differenced version (4) is the base. We add p lags of the dependent variable (Δy_t), accounting for dynamics in our model, more specifically the intent is to remove any serial correlation in Δy_t. If we did not account for autocorrelation when it was present, we would be ommiting an independent variable in our regression. This would have direct consequence on the efficency of our estimation, as it would no longer be unbiased. Missing explanatory variable is a direct violation of the contemporaneous exogeneity assumption (one of the Gauss-markov assumptions) of $E(\epsilon_t|x_{t_1}, x_{t_2}...x_{t_n}) = 0$. The other two conditions of linearity of parameters and of no perfect colinearity are fullfilled, therefore correcting for serial correlation implies that we can use the t-statistic for testing our hypothesis. Not accounting for them results in invalid significant tests. The ADF test has the following form:

$$\Delta y_t = \alpha + \beta t + \theta y_{t-1} + \sum_{i=1}^{p} \rho_i \Delta y_{t-i} + \epsilon_t \tag{5}$$

where β is now the coefficient of time trend, θ again is the coefficient of the lagged y_t variable and $|\rho_i| < 1$. The same hypothesis can be tested and the same significance level apply. The critical values of the regression as seen in (5) for 1%, 5% and 10% levels of significance are -3.96, -3.41, -3.12, respectively. Against these levels we can use the t-statistic from performed OLS regressions.

Now as we have defined stationarity and process integrated of order d, we can move to the main part - cointegration of two or more time series. We, can therefore, introduce co-integration as has been originally presented by Engle and Granger (1987):

> The components of the vector y_t are said to be co-integrated of order d,b, denoted $y_t \sim CI(d,b)$ if (i) all components y_t of are $I(d)$; (ii) there exists a vector $\alpha(\neq 0)$ so that $z_t = \alpha' y_t \sim I(d-b), b > 0$. The vector α is called co-integrating vector.

We can now formulate an example to illustrate the importance of co-integration of vectors in spread mean reversion strategies. Let us have two outright contracts of Brent crude oil and heating oil, both expiring in September 2015. We run the ADF test on them only to fail to reject the null hypothesis of a unit root. Now, the two time series could potentially be both I(1), their cointegration by definition would then result in a stationary, I(0) process. At this point, we still lack the methodology for determining whether or not the series are in fact co-integrated, hence we will define it next. Engle-Granger (EG; AEG is also used where A stands for its augmented version) test is a two-step method:

1. After testing the series y_{1t}, y_{2t} for unit root (and failing to find them stationary), running the OLS regression $y_{1t} = \beta y_{2t} + \epsilon_t$ and saving the residuals $\hat{\epsilon}_t$

2. Second regression of $\Delta\hat{\epsilon}_t = \mu + \hat{\epsilon}_{t-1} + \eta$, including possibly multiple lags of $\Delta\hat{\epsilon}_t$ for the augmented version of EG test.

As we can see, the second part of the AEG test is the already known ADF test for unit-root. In this case, we are testing for stationarity of the residuals from the first regression (using equation 5), the same critical levels apply. The null hypothesis in the AEG test is that the series y_{1t}, y_{2t} are not co-integrated. The second part of AEG test is crucial, skipping it could leave us with a two spurious regressions, that is those which do look good on paper (High R^2, significant coefficients), but mainly because of the fact that they trended over time in the same direction, not because they are fundamentally related. Especially with commodities, we could find relationships between commodities which have no economic meaning, only because they both tended to trend over time.

4.2 Filter Trading Strategies

Once a co-integrated spread is identified, trading it becomes relatively easy. We will be using the standard filter method and we will also try to enhance it slightly with a use of a time series analysis referred to as the Relative Strength Index (RSI). Let us say that we found the WTI-Brent spread to be co-integrated. The standard filter approach says that we should long the spread (buying WTI, selling Brent) when $WTI < \beta * CL + X$ and short it if the other equality is true. β is the co-integration parameter and X is the standard filter in the level of fair value. Increasing the size of X typically yields fewer trades with higher average size of both profits and losses. X will be optimized, we will be taking multiples of standard deviation of the spreads. As in this case we would enter the trade once the market is moving away from its equilibrium, this might evoke the idea that we are trying to "catch the falling knife". Instead, we could employ the RSI, which is an indicator designed for rotating, oscillating markets. RSI is calculated as follows:

$$RSI = 100 - \frac{100}{1 + RS} \tag{6}$$

where RS is

$$RS = \frac{SMMA(U, n)}{SMMA(D, n)} \tag{7}$$

where SMMA is the smoothed moving average (it is the same as exponential moving average, where $\alpha = \frac{1}{n}$) of closing prices, for the upward and downward changes. In the case of an upward change, U is calculated as the difference between current close and previous close and D is 0. The opposite is true in the case of a downward change. The RSI indicator oscillates between values 0 and 100, where zone below 30 is generally regarded as 'oversold' and zone above 70 as 'overbought'.

The idea of combining the filter approach and RSI should ideally result in filtered signals and lower drawdowns. That is mainly because of the fact that we would enter the position only if RSI was crossing from the oversold area (below 30) and at the same time, the market would be below its fair value by X. The same idea holds for shorting the spread. RSI would generate signals only once the market starts moving back towards its equilibrium. The trades will be closed once market achieves its equilibrium again. This is something we will come to back later, as even though this approach is usually employed in the academic spheres, it has quite strong drawbacks which we will try to correct.

4.3 Moving averages

The main drawback of the co-integration method is also the reason why we were so eager to look into it in the first place - the resulting time series is stationary. There are many factors, which could make any economic relationship that exists between the contracts obsolete. In case of commodities, only a handful of market participants (or countries) could over short period of time very significantly influence the price by either shutting down a facility or declaring tariff on some of the goods as an act of protectionism (e.g. China as the largest Soybeans importer could impose tariffs such that world's soybean supply would increase disproportionately). This can be to a certain degree corrected with the approximated version of fair value - moving average (MA). The MA in time t of period N will be calculated using its simple version:

$$MA_t(n) = \frac{\sum_{t-n}^{t} p_{t-n}}{n} \tag{8}$$

where we are summing the n last prices at time t and dividing them by the number of periods - n. Trading this strategy is again straight forward. As we will be using this rule in spreads which we expect to be mean-reverting, it only makes sense to buy the spread once its trades below its moving average and sell it in case it trades above it. Markets which are not stationary, in which trends can be identified the opposite would be true, as we would want to catch moves away from current 'value'. Again, we will be testing various filter levels in-sample, they will have the same structure as in the previous trading strategy. Therefore we will buy the spread if $p_t + X < MA_t(n)$ and sell it when the opposite inequality is true: $p_t + X > MA_t(n)$. It is important to note that the size of the filter on the upside and on the downside can differ significantly. Although this behaviour is more prone to exist in the stock market, where down moves are often substantially more volatile than bullish moves.

4.4 Seasonality

Seasonality is usually an effect we want to get rid off in regressions in order to figure out what the effect of a specific policy or event was. As we saw in the literature section, financial markets have in the past been showing strong seasonality patterns, forming spreads around these tendencies is just an attempt to capitalise on these tendencies with very naive buy and hold trading strategies. For simplicity sake, we will be studying only two-legged spreads, which are at maximum one year apart in terms of their expiration. Simple regression analysis will be conducted:

$$y_t = \alpha + \beta_1 t + \sum_{i=2}^{52} \beta_i \text{Week Dummy} + \epsilon_t \tag{9}$$

where β_1 represents the time trend and $\beta_2 - \beta_{52}$ will be the coefficients of dummy variables every week with the exception of week number 52.

Based on (9) we will be generating simple naive buy and hold trading strategies. The easiest case is the one where the regression yields at least one week with a negative and one with a positive significant coefficient at least at the 5% significance level. Then the strategy would be to buy (sell) in the lowest (highest) point and sell (buy) it again at the highest (lowest). We will mark these strategies as "2extremes". Next, "1extreme" strategy will be created and tested, they will consist of buying (selling) the spread in the highest (lowest) significant week and selling (buying) the spread at least three weeks before or after the extreme week.

4.5 General notes - trading

We will be using the settle prices in all mentioned contracts, with the assumption that we will be able to enter the position exactly at this price. As is the convenience in academic literature, we will be excluding the highs and lows from the trading days. Trading is not a frictionless endeavor and as such we will need to account for fees and commissions paid to the exchange and to the broker who is the intermediary between us and the various exchanges. For simplicity sake we will be assuming \$10/RT (round turn - both buying and selling of one contract, that implies twice the amount of \$10/RT for any given spread consisting of two legs with one contract on each), which is higher than current least expensive discount brokers, but it leaves some space for occasional slippage which could occur, hence this amount should be on average quite realistic. In case of inter-commodity spreads, roll overs are necessary and therefore we will use \$70 as an approximation to possible position rolls and accompanying fees. We do not expect any other costs of doing business given that we have used a publicly available database and that there is no need of larger investment (such as infrastructure) on the trader's side.

5 Empirical results

5.1 Mean reversion

5.1.1 Preliminary analysis

We will be first looking into the in-sample period of January 1st, 2000 - December 31st, 2011. The exception form spreads containing RBOB Gasoline futures (RB), where the in-sample period will be shifted to November 1st, 2005 - December 31st, 2013 and Russell 2000 e-mini (TF) where the in-sample starts November 1st, 2001, the rest remains unchanged. The two named are excluded out of the main table and ADF test of contracts over the same time span have been conducted separately. The cattle and soybean crush spreads will be tested for stationarity in a slightly different manner than other spreads as in their case we will be using time series based on Table 3 and 2, respectively. In other products, the standard continuation contracts will be used. The ADF test with three lags of the dependent variable has been used, the results for all products are summarized in Table 4 and the special cases of products of the soybean crush and cattle spread can be seen in Table 5.

Using the ADF test we could not reject the null hypothesis of stationarity in most of the continuous data of our products, with the exception of live cattle and lean hogs at 5% significance level, and swiss franc along with 30Y US T-Bond at the 1% significance level. Looking at the ADF tests conducted on the special case spreads, we can see that live cattle does not give enough evidence for rejecting the null hypothesis. Soybean meal, on the other hand, is stationary at the 10% significance level. Looking at results of windows around RB and TF contracts, we had to exclude lean hogs and 30Y US T-Bond in the case of Russell 2000 e-mini and lean hogs in the case of RBOB Gasoline.

We can now take the remaining contracts which are not stationary at least at the 5% significance level and test them for cointegration. This yields more than one thousand spreads, Table 6 (still excluding RB and TF) only shows the ones where the ADF t-statistic is significant at the 5% significance level. Not surprisingly a large number of spreads returned significant coefficient estimates in the first OLS regression but failed to return them significant in the residual regression. The cointegrated spreads in Table 6 are partly ones we have mentioned, such as various types of crack spread, we also see agricultural spreads - combinations of wheat, soybean oil, corn and "Hard Red Winter" wheat. Surprisingly we also see that some spreads which seemingly do not have any direct economic relationship are also cointegrated. Examples of such spreads is Cotton and Silver (CT-SI) or Australian dollar - Feeder cattle (AD-FC). Last important thing, the estimate of the coefficient from the first regression also serve as a ratio in which we will be building the spread. In stocks, we would be able to build the spread more precisely, as buying an individual stock is usually less capital intensive than opening hundreds of futures positions. Because of that, we will be facing slight residual risk due to the position not being completely in line with the cointegration coefficient. We will also skip some of these spreads, as the cointegration coefficient yields a position that would be too capital intensive (buying or selling disproportional amount of one contract). Otherwise, we will round the coefficient to closest multiple of 0.25 and use that as an approximate ratio. We have excluded from the table and from our analysis in general commodities which are co-integrated but yield a highly disproportional coefficients as this would result in extremely high fees per trade and such spreads (all containing EuroDollar - ED)

5.1.2 Trading strategy results

Two of the three mean reverting strategies (not counting moving average) employ the standard filter based on the distance of residuals from the fair value. We will use the in-sample period to run some basic optimization techniques, testing for the optimal profit, stop loss and distance of the residual from the fair value. We have conducted these tests separately for long and short positions, as due to the nature of some spreads the opportunities on the long and the short side could be asymmetric. The strategy based purely on the fair value filter will be further divided into two - the entry signals remain the same, but in the first strategy called Filter0 we will be closing the position either if a stop loss is triggered or if the residual returns back to the fair value. The other strategy simply called Filter will also have a stop loss in place, but we will not exit the position once the residual returns back to value, rather we will be taking a fixed profit based on the multiple of the standard deviation of the spread series. In the case of Moving average strategy, we will be optimizing for the deviation of the spread from its moving average. The optimization range goes from 0.5 to 2 by 0.5 increments in case of profits, stop loss and filter values will be tested from 0.2 to 1.4 standard deviation with 0.2 increments. The RSI and Moving average values will be left constant with 14 being the period of RSI, 70 and 30 the levels where RSI indicates "overbought" and "oversold" areas and the moving average will have a constant period of 50 days.

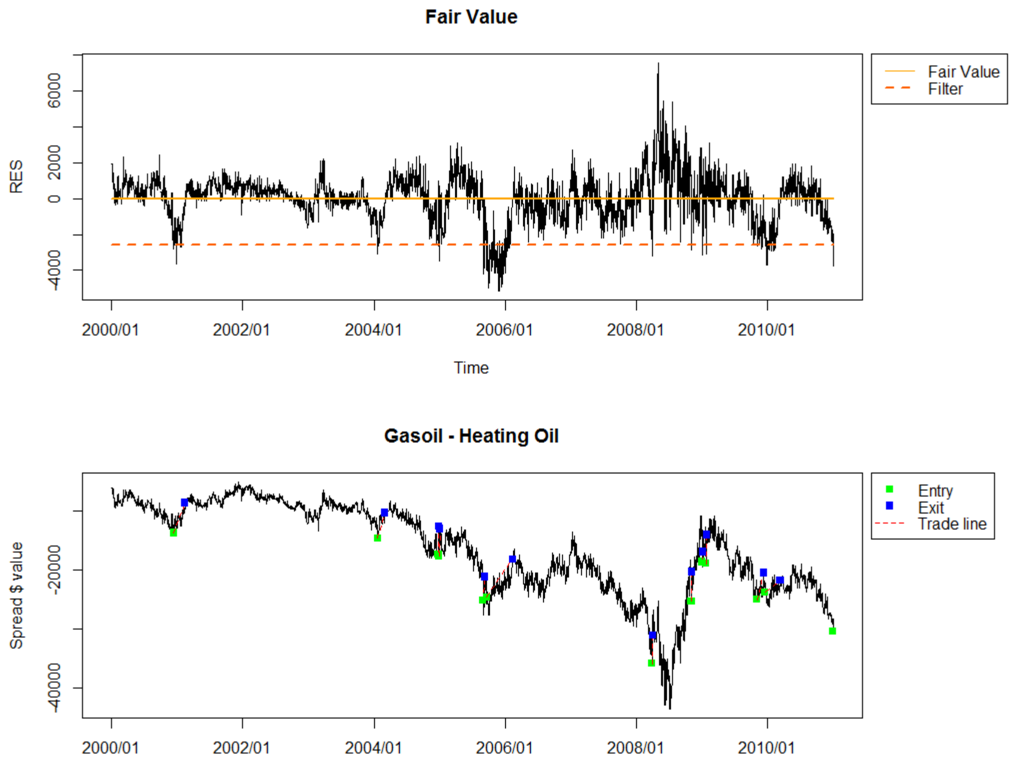

Figure 3: Visualisation of Filter0 Long Strategy

Figures 3 is a visual representation of the Filter0 strategy. The upper chart represents the residuals, where the orange horizontal line at $y = 0$ corresponds to the fair value. The orange dashed line represents the filter value, that is once market trades below (above) in case of long (short) position an entry signal is triggered. As we can see, around the year 2001 we have crossed below the filter value for the first time. On the lower chart where we can see the actual spread there is first entry signal (marked green, as we are looking for long signals only) on the day the filter threshold has been crossed. We got out of this position with a profit as a few weeks later we traded back to the fair value. Similar graph could be generated for the Filter strategy, we, however, would have most likely a different exit, depending on which multiple of the standard deviation of the spread we will be testing.

Results of the four strategies (Filter0, Filter, RSI strategy and MA strategy) are summarized in Tables 7, 8, 9 and 10, respectively. First four to five columns are the input parameters, rest is the output based on trades for the given strategy. The stop loss (SL) and profit (PT) are multiples of the standard deviation of the spread. Similarly stanard deviation (SD) can be either a multiple of the standard deviation of the spread (as is the case with moving average strategy) or a multiple of the std. deviation of the spread itself (as it is the case of RSI, Filter and Filter0 strategies). Next we have column identifying whether these parameters have been tested for the long or the short side. Spread column is self exaplanatory, spreads consisting of either RB or TF take data from their respective in-sample periods. Max win and loss columns record the single biggest winning and losing trades. Win rate is the percentage of winning trades out of all the trades for a given strategy. Last, Sharpe ratio is a statistic approximating the true Sharpe ratio. But instead on focusing on relative daily returns on portfolio from which we subtract the risk-free rate and divide the whole by the standard deviation of the return of the portfolio, we simply take the mean of all of our trades and divide it by the standard deviation. Going forward, strategies based on higher adjusted Sharpe ratio should yield more consistent results in the out-of-sample period than strategies with the highest average profit. The Draw down (DD) metric indicates the maximum dollar decline in equity we would have experienced trading this strategy. For instance, in Table **??** the first spread between Australian Dollar (AD) and feeder cattle (FC) had a drawdown of more than $45,000. But looking at maximum loss and percentage of wins, the drawdown metric is substantially larger. Looking more closely, we can see that the stop loss (SL) parameter was a 1.4 multiple of the standard deviation. Therefore, in the end, our maximum loss was relatively small, but at one point we had large unrealized loss. This suddenly makes us look more realistically at this strategy, as the risk of unrealized loss turning into realized one is significant.

Looking at the general results, we can clearly see that some of the strategies for trading inter-commodity spreads are capital intensive. There are three main reasons for that, first, inter-commodity spreads, in general, tend to move more than their intra-commodity counterparts. That is due to the fact that we are dealing with two different (even though sometimes related) commodities and as such these can quite easily diverge significantly from their short run equilibrium. Next, as we wanted to minimize the residual risk we are taking larger than normal positions. In some cases, this can result in 3 contracts in one leg and 4 in the other, as is the case of AD-FC. Solution for that would be quite simple, decreasing of the position size, in this case we would open only one contract in each leg. Bearing in mind that the trade-off dictates that lower position also means higher residual risk. Last the in-sample window contains data from the 2007-2008 financial crisis which directly effected (or has been effected by) various futures contracts which we study here. Looking at Table 7 we can see that the Brent - Heating oil (B-HO) long position had an extreme winner of little more than $119,000. This trade occurred right after Brent (and WTI) crude oil reached its peak in 2008 of more than $140 per barrel. Similarly cotton was near its all time high at the end of our period, E-mini S&P500, Dow Jones and Russell contracts all suffered heavy losses during the crisis. Going forward we might consider lowering our stops and profit targets accordingly if the out-of-sample period turns out to have significantly lower overall volatility.

For each strategy, we wanted to see the at least 10 trades for any given spread in any of the two directions. Our in-sample period is quite long and this would leave us with strategies yielding at minimum one trade annually per side (long/short). Although the sample size of our trades is not ideal it is a direct consequence of the strategies and time frame we picked. Some of the holding periods span over multiple months and larger deviations from the mean are not as common as we would want them to be. We then show strategies which display highest Sharpe ratio. In most of the spreads, we were able to find profitable strategies, at least in the in-sample window. We can also see that the results show two main types of strategies - high probability rate with higher amounts on stop losses than on profit targets and lower probability trades where the opposite being true. This nicely illustrates another trade-off we have to face when choosing the strategies - the trade-off between risk to reward ratio and the winning trade percentage. This could be extended to "Draw down impossible trinity", recalling back the AD-FC strategy example. This would imply that profitable strategy can have only two out of three features - low drawdown, high risk to reward (RRR) ratio or high winning percentage. It will be interesting to see how various types of strategies will perform on average in the out-of-sample data set.

There are a couple more general observations we can make when looking at the data. First, stock indices spreads tend to have smaller average profit than the rest of spreads, these products even though different are very similar in structure and therefore do not diverge as much from their equilibrium. They are specific as very few events could cause the price of one index diverge significantly from the other (one of the exceptions is the Dot-com bubble, where the technology stocks dropped more than an average stock).

Given that the tested spreads were cointegrated, it is not as difficult to find a profitable mean reverting strategy on past data. There are a few exceptions to this rule and there is no point in keeping the unprofitable strategies for the out-of-sample test, as clearly we could not even find a profitable strategy for given spread in the in-sample period. It is therefore only logical that we want to test the profitable strategies on different time periods. If the parameters of some given spread yield positive expectancy both in in-sample and out-of-sample periods, we might consider them for future trading.

5.1.3 Out-of-sample

The in-sample period enabled us to optimize the parameters with respect to the respective Sharpe ratio. The out-of-sample period is there to test the robustness of our strategies and of their parameters. We ran an OLS regression in the in-sample period for each spread, the coefficient served us as an approximation of the ratio legs of the spread. Similarly, the residuals from this regression were the basis of the fair-value filter. For us to test the robustness, we will be using the coefficients from the in-sample period in the out-of-sample tests. Running a separate OLS regression on the OOS would go against the logic of testing of robustness, as after all, we want to know whether the parameters from IS hold in OOS as well. We will, therefore, take the coefficient from IS, apply it on the time series in OOS and doing so will result in a newly computed spread. The residuals will be taken as a difference between the legs of the spread multiplied by the IS coefficient. Similarly, the standard deviation multiples will not be relative in size to the standard deviation of the OOS spread, we will take the values as absolute from the IS analysis. This corresponds to the profit, stop loss and standard deviation regarding both the spread and the residuals.

Tables 11, 12, 13, 14 summarize the results of the four mean reverting strategies. We only display results of strategies with more than 5 trades, the number is smaller this time as the OOS period is shorter. Spreads with less than 5 trades are automatically disregarded as they do not meet the required minimum. Out of 124 spreads in Filter0 63 strategies yield more than 5 trades and 44 have positive average profit. Filter has a total of 144 spreads, 69 with at least the minimum of trades, 53 also have positive average profit. RSI have 80, 63 and 40 spreads, MA strategies 124, 68 and 24 spreads, respectively.

Interestingly enough, we drop most strategies when applying the minimum trade condition. The drop from all trades only to the profitable ones is usually not as dramatic, with the exception of moving average strategies.

Looking at the overall profitability, disregarding the minimum number of trades condition, the trading strategies have 77, 89, 40 and 46 profitable spreads. Again with the exception of MA, at least 50% of the strategies are profitable. Paradoxically the only strategy based on relative, flexible fair value performed the worst. On the following figure we can see a spread, which is no longer stationary.

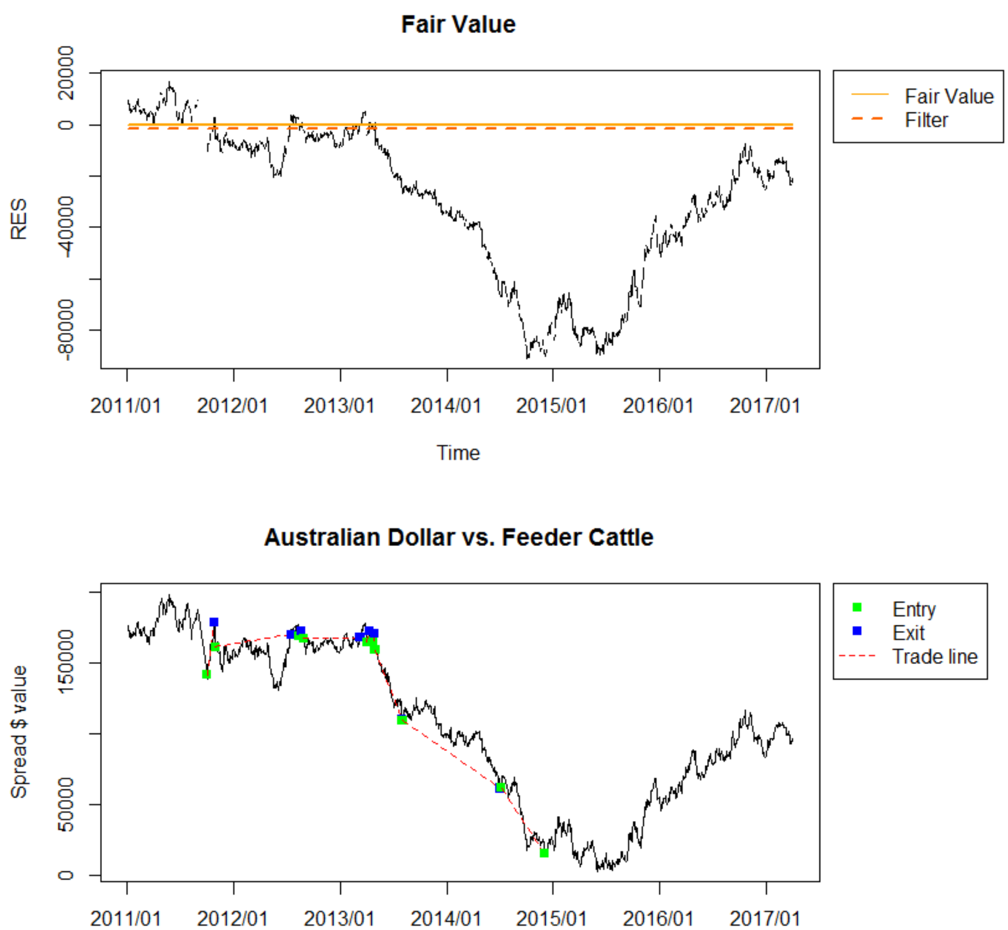

Figure 4: Visualization of out-of-sample AD-FC Trade

The filter0 strategy yielded negative results, as it kept buying the spread all the way to the bottom. The MA strategy with slightly different parameters delivered unsurprisingly similar (hence negative) results. Generally speaking, there are three main outcomes in the out-of-sample analysis. The first one yields no representative results, due to lack of trades on either side. This is mainly caused by lower volatility in the out-gof-sample period, which is in accordance with the already mentioned fact that the in-sample period contained very turbulent times following the financial crisis of 2007/08. Next case is represented by spreads where we have enough trades in only one direction. That would be the case of Figure 4, where we entered enough long trades but only a couple of shorts due to the trend which has developed within the spread. This asymmetry can yield both positive and negative results, but either way, the general underlying of the spread has apparently changed and as such is not tradable in the future. At least not with the same parameters. Last remain spreads which yield positive results in both directions. This implies that the spread parameters withstood the test of OOS testing period. Interestingly enough, majority of these kinds of spreads are formed out of similar commodities. We can see combinations of various agricultural or petroleum based spreads among them. This narrows down our list further but is logical in the sense that truly related commodities are more likely to keep a steady cointegration relation. Due to poor performance, we also have to disregard the MA strategy altogether.

5.1.4 Notable case spreads

The results for spreads which have been mentioned in part 3.2 have been partially covered in the last subsection. Those were the ones consisting only of two legs. We have however also mentioned spreads which were three-legged. Among other things, these spreads are the industry standard, we will, therefore, ignore their OLS regression coefficients and instead we will use the "industry" numbers. Therefore similar approach to computing residuals as in OOS period will be used. We have tested total of 8 three legged spreads. The Cattle and Crush spreads are the 2-1-1 and 1-1-1 variations, respectively. Crack spread has used either WTI or Brent crude oil contract - spreads with Brent are marked with letter B at the end of their name.

Other than that, the ratio of the contracts is marked with the three numbers. Table 15 displays the results of in-sample analysis, Table 16 contains data for out-of-sample period. As we can see, we were successful in generating profitable strategies inside the IS period, however, failed to demonstrate similar qualities of our strategies in the OOS period.

6 Seasonality

We will divide intra commodity spreads into two samples, in this way we can again conduct an in-sample and out-of-sample analysis. The in-sample period ends in the year 2013 (Spreads containing RB or TF will therefore have shorter in-sample period) As we have already mentioned, we will only consider spreads which are at most one year apart from another in terms of their expiration. Again, we will compute all spreads which fulfil this condition and we will aggregate them by transforming them into general form of Ticker_1 Year_1 / Ticker_2 Year_2, where ticker symbols are always of one commodity only and year 1 and 2 could be either a combination of X/X (same year) or X/Y (second leg is further apart). An example of such spread can be seen in Figure 5.

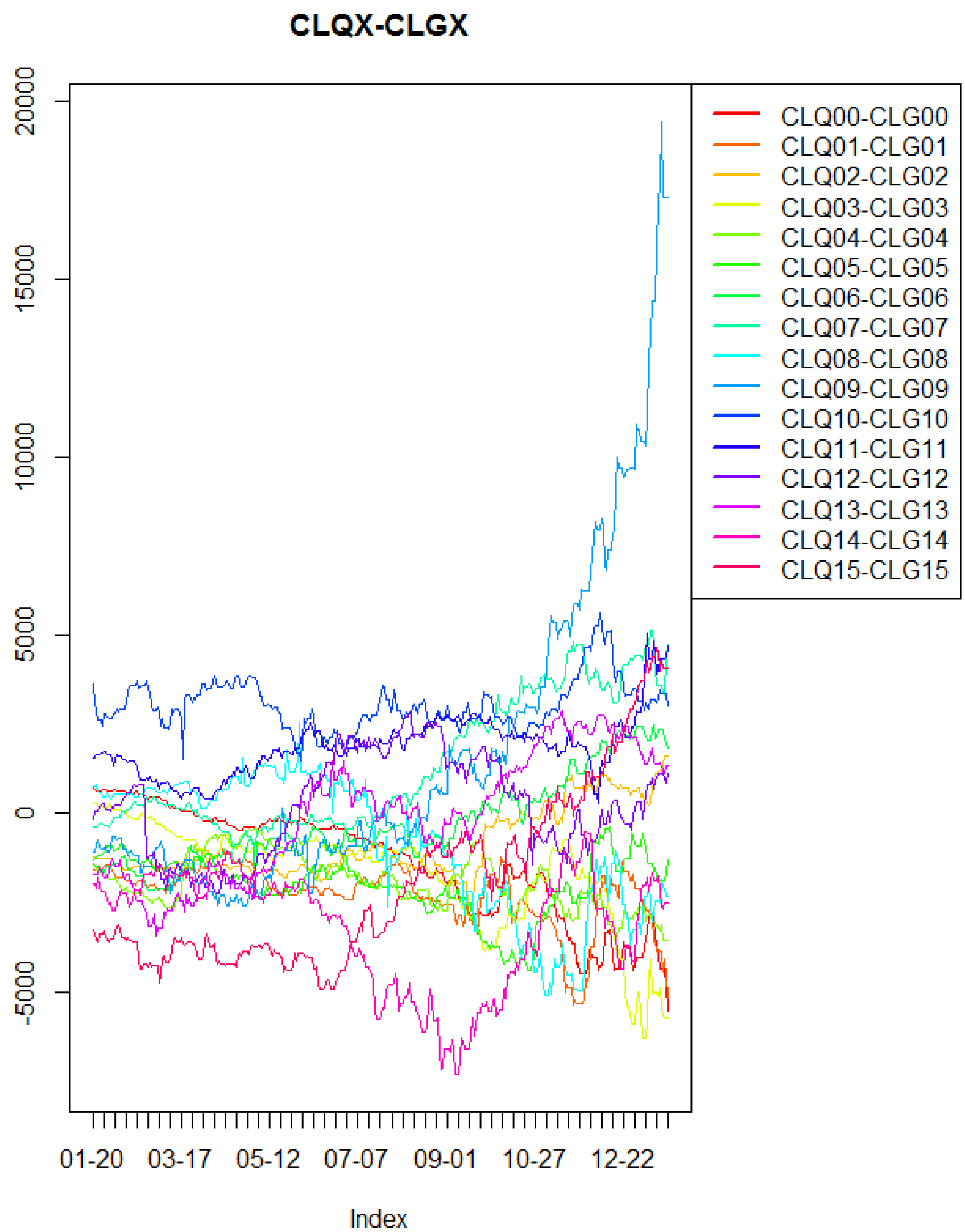

Figure 5: Visualisation of seasonal WTI Crude Oil Spread

Here we were able to aggregate all contracts starting with CLQ00-CLG00 and ending with CLQ15-CLG15 into the general form of CLQX-CLGX. The X axis represents the development of these spreads for every single year and each year is marked with different color. We have generated a total of 2124 intra-commodity spreads, excluding those whose shortest year is shorter than

100 days. This has greatly reduced the number of spreads, mainly excluding spreads which are far apart from one another and therefore intersect only for a short period of time. Lastly, we have reduced the number of days for every contract to 365 so that for every year every date (day and month, excluding year) appears only once. Also, we have excluded the last week before last trading day, as that is when the spread can get very volatile and illiquid.

The equation (9) has been used to test seasonality of these spreads and if some coefficient turned out to be positive, the mentioned strategy has been tested and optimized again, for the same Sharpe ratio we have used before. Unprofitable spreads have been again disregarded in the out-of-sample period. In the in-sample, we have also ignored the most profitable year for any given spread. Calendar spreads tend to have from time to time one extreme year due to undersupply or oversupply of the underlying commodity. We do not want the in-sample performance to be influenced by any one trade and such large positive trade could very well make an otherwise unprofitable spread get into the black. Again same rules with disregarding unprofitable in-sample trades in the out-of-sample period apply. In the out-of-sample period, the number of trades differ spread by spread, as we only included a given year, if there were already data for both entry and exit dates.

The results are due to the table size summarized in an attached PDF file. In the in-sample period, we managed to find positive strategies in 89% of spreads. As we can see from the table, a vast majority of spreads is from agricultural or energy sector. We do not see any T-bills or stock indices to exhibit strong seasonality. Some of the commodities had significant results in the OLS regression, even though we would not expect these commodities to be seasonal in nature. These include gold, silver, and copper and together with soybeans oil, these spreads are not worth trading, given the overall very narrow range of the spreads. The narrow spread is a direct consequence of the properties of these commodities - they are easily storable for longer periods of time and therefore their supply and demand is much more predictable and stable.

As we have already mentioned, the average size of calendar spreads trade is much lower than of almost any of the inter-commodity spreads. There are two main reasons for that - first, the calendar spreads consists of two one-contract legs. The ratio of legs in inter-commodity spreads had to be adjusted according to the ratio we got from the OLS regression. Secondly, we are dealing with the same underlying asset in both contracts. The contracts differ only in the date of delivery, otherwise they have to be the same due to the specification of futures contracts.

In the OOS period, 60% of spreads were suprisingly still positive, however the average profit has decreased in 69% of the cases. Although we managed to find some profitable strategies in both testing periods, additional test and optimization will be necessary. Naive buy (sell) and hold trading strategies can yield positive results in some of the spreads, but based on the data we have, there is hardly a way for us to subset strategies which we can expect to be profitable going forward. There are no obvious outliers in terms of products, their contracts or types of strategies (1 vs 2 extremes). Rather than simple buy and sell strategies the time parameter can be used more as a filter, where the entry and exit signal will be generated based on some other information, such as price behavior or deviation from the seasonal norm. Given our technique, we did not manage to find profitable patterns in naive purely time-based strategies. This does not necessarily imply that all tested spreads are efficient from the point of view of seasonality. We can only conclude that about the commodities which have had very narrow spreads over the years - be it silver, gold or platinum. Given our transaction cost, there is simply no seasonal strategy worth pursuing.

7 Conclusion

Spreads have been historically quite a popular theme amongst academics and it was worth looking into various strategies and their effectivness in recent years. We have tested two main types of approaches - seasonality and mean reversion. Seasonality tests have been conducted on calendar spreads - their main advantage is they are relatively less riskier than outright positions. Simply buy-and-hold strategies, however, failed to deliver desired results. More specifically there were strategies which were profitable in both IS and OOS periods, but I did not manage to find a reliable pattern that would allow us distinguish between winning and losing spreads. Mean reversion spreads have been tested on two-legged (mostly generic) spreads, as well as on 3-legged spreads well known in the trading industry. The former yielded robust strategies on spreads which are not only co-integrated but also have an underlying economic significance (such as constituencies of two-legged variations of the crack spread). The latter failed miserably in the out-of-sample period, one of the reasons is possibly the fact that we have used the industry coefficient, not ones generated based a OLS regression as was the case in 2-legged spreads.

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Appendix

Table 1: List of all products

BO	Soybean Oil	Grain/Oilseed	FHKNQUVZ	2000
C	Corn	Grain/Oilseed	HKNUZ	2000
HG	Copper	Metal	FGHJKMNQUVXZ	2000
O	Oats	Grain/Oilseed	HKNUZ	2000
S	Soybeans	Grain/Oilseed	FHKNQUX	2000
SM	Soybean Meal	Grain/Oilseed	FHKNQUVZ	2000
W	Wheat	Grain/Oilseed	HKNUZ	2000
SI	Silver	Metal	FGHJKMNQUVXZ	2000
LC	Live Cattle	Meat/Livestock	GJMQVZ	2000
PL	Platinum	Metal	FJNV	2000
CC	Cocoa	Food/Fibre	HKNUZ	2000
FC	Feeder Cattle	Meat/Livestock	FHJKQUVX	2000
LB	Lumber	Food/Fibre	FHKNUX	2000
GC	Gold	Metal	FGHJKMNQUVXZ	2000
BP	British Pound	Currency	HMUZ	2000
SF	Swiss Franc	Currency	HMUZ	2000
JY	Japanese Yen	Currency	HMUZ	2000
KW	Wheat KCBT	Grain/Oilseed	HKNUZ	2000
PA	Palladium	Metal	HMUZ	2000
CD	Canadian Dollar	Currency	HMUZ	2000
US	30Y US T-Bond	Interest Rate	HMUZ	2000
HO	Heating Oil	Oil/Energy	FGHJKMNQUVXZ	2000
ED	Eurodollar	Interest Rate	FGHJKMNQUVXZ	2000
CL	Crude Oil	Oil/Energy	FGHJKMNQUVXZ	2000
TY	10Y US T-Note	Interest Rate	HMUZ	2000
DX	U.S. Dollar Index	Index	HMUZ	2000
AD	Australian Dollar	Currency	HMUZ	2000

Ticker	Name	Category	Months	Year Start
RR	Rough Rice	Grain/Oilseed	FHKNUX	2000
FV	5Y US T-Note	Interest Rate	HMUZ	2000
NG	Natural Gas	Oil/Energy	FGHJKMNQUVXZ	2000
B	Brent Crude Oil	Oil/Energy	FGHJKMNQUVXZ	2000
TU	2Y US T-Note	Interest Rate	HMUZ	2000
NE	New Zealand Dollar	Currency	HMUZ	2000
ES	S&P 500 mini	Index	HMUZ	2000
YM	mini-sized Dow $5	Index	HMUZ	2000
EC	Euro FX	Currency	HMUZ	2000
NQ	Nasdaq 100 mini	Index	HMUZ	2000
CT	Cotton #2	Food/Fibre	HKNVZ	2000
SB	Sugar #11	Food/Fibre	HKNV	2000
OJ	Orange Juice	Food/Fibre	FHKNUX	2000
KC	Coffee	Food/Fibre	HKNUZ	2000
RS	Canola	Grain/Oilseed	FHKNX	2000
G	Gas Oil	Oil/Energy	FGHJKMNQUVXZ	2000
TF	Russell 2000 mini	Index	HMUZ	2002
RB	RBOB Gasoline	Oil/Energy	FGHJKMNQUVXZ	2006
LN	Lean Hogs	Meat/Livestock	GJKMNQVZ	2000
W	White Sugar	Food/Fibre	HKQVZ	2000

Table 2: Crush spread - roll over

Roll	Soybeans	Soybean Oil	Soybean Meal	First Day	Last Day
1	January	January	January	Nov 1st	Dec 31st
2	March	March	March	Jan 1st	Feb 28th/29th
3	May	May	May	Mar 1st	Apr 30th
4	July	July	July	May 1st	Jun 30th
5	September	September	September	Jul 1st	Aug 31st
6	November	December	December	Sept 1st	October 31st

Table 3: Cattle spread - roll over

Roll	Feeder Cattle	Live Cattle	Corn	First Day	Last Day
1	January	June	March	Nov 1st	Dec 31st
2	March	August	May	Jan 1st	Feb 28th/29th
3	April	August	May	Mar 1st	Mar 31st
4	May	October	July	Apr 1st	Apr 30th
5	August	February	September	Jun 1st	Jul 31st
6	September	February	December	Aug 1st	Aug 31st
7	October	April	December	Sep 1st	Sep 30th
8	November	April	March	Oct 1st	Oct 31st

Table 4: Results of ADF test on in-sample data

Root	ADF Level	ADF Differenced	Root	ADF Level	ADF Differenced
AD	0.27	0.01	LN	0.01	0.01
B	0.49	0.01	NE	0.49	0.01
BO	0.64	0.01	NG	0.39	0.01
BP	0.89	0.01	NQ	0.42	0.01
C	0.56	0.01	O	0.43	0.01
CC	0.10	0.01	OJ	0.66	0.01
CD	0.26	0.01	PA	0.99	0.01
CL	0.44	0.01	PL	0.44	0.01
CT	0.99	0.01	RB	0.30	0.01
DX	0.47	0.01	RR	0.38	0.01
EC	0.54	0.01	RS	0.65	0.01
ED	0.95	0.01	S	0.45	0.01
ES	0.57	0.01	SB	0.95	0.01
FC	0.25	0.01	SF	0.09	0.01
FV	0.50	0.01	SI	0.97	0.01
G	0.56	0.01	SM	0.14	0.01
GC	0.83	0.01	TF	0.68	0.01
HG	0.66	0.01	TU	0.75	0.01
HO	0.51	0.01	TY	0.16	0.01
JY	0.51	0.01	US	0.01	0.01
KC	0.60	0.01	W	0.42	0.01
KW	0.48	0.01	WS	0.91	0.01
LB	0.25	0.01	YM	0.45	0.01
LC	0.02	0.01			

Table 5: Results of ADF test on in-sample data in cattle and soybean crush spread

Root	ADF Level	ADF Differenced
S	0.280	0.01
BO	0.430	0.01
SM	0.060	0.01
FC	0.450	0.01
LC	0.420	0.01
C	0.390	0.01

Table 6: Cointegration test.

Spread Ticker	ADF t-statistic	Coefficient	Spread Ticker	ADF t-statistic	Coefficient
AD-FC	-3.68	1.47	KW-O	-3.63	2.3
B-CL	-4.19	0.99	KW-RR	-3.82	1.23
B-HO	-3.76	0.84	KW-RS	-3.56	3.23
B-KW	-3.58	2.27	KW-S	-3.56	0.62
B-NG	-3.54	0.85	LB-NE	-3.59	0.48
B-PL	-3.48	1.08	LB-NG	-3.63	0.44
B-W	-3.55	2.39	O-W	-3.74	0.44
BO-C	-4.19	1.14	PL-W	-3.51	2.2
BO-KW	-4.46	0.73	RR-S	-3.98	0.5
BO-RR	-3.6	0.91	RR-SM	-3.99	0.83
BO-W	-4.78	0.77	RR-W	-3.94	0.82
BP-NG	-3.51	1.57	RS-W	-3.83	0.31
C-KW	-4.07	0.63	S-W	-3.76	1.64
C-O	-3.7	1.48	SF-TU	-3.64	0.47
C-RS	-3.78	2.08	SF-TY	-3.82	0.89
C-W	-4.12	0.66	TU-TY	-4.53	1.88
CD-FC	-3.7	1.64	ES-TF	-3.54	1.76
CL-G	-3.58	1.15	LB-TF	-3.92	0.74
CL-HO	-4.21	0.85	NG-TF	-3.71	1.11
CL-KW	-3.48	2.3	TF-YM	-3.61	0.64
CL-NG	-3.62	0.86	CL-RB	-3.68	0.83
CL-PL	-3.57	1.1	G-RB	-3.54	0.77
CL-RR	-3.48	2.92	HG-RB	-3.52	0.81

CL-W	-3.48	2.43	HO-RB	-3.86	1.04
CT-SI	-3.46	4.99	KW-RB	-4.17	0.34
FC-LB	-3.58	1.57	NG-RB	-3.45	0.5
FV-SF	-3.62	1.09	O-RB	-4.39	0.15
FV-TY	-5.23	0.98	PA-RB	-3.74	0.58
G-HO	-3.97	0.74	PL-RB	-3.67	0.71
G-KW	-3.47	2	RB-RR	-3.63	3.54
G-NG	-3.56	0.75	RB-S	-3.51	1.67
HG-OJ	-3.46	3.15	RB-SM	-3.47	2.75
HO-NG	-3.49	1.02	RB-W	-3.86	3.02
KC-SI	-3.78	0.69			

Table 7: Filter0 trading results on in sample data

SL	SD	L/S	Spread	Avg $	Max Win	Max Loss	Win%	#	DD	Sharpe
1.4	0.2	Long	AD-FC	$6,063	$16,080	$-7,400	0.87	15	$45,050	0.91
1	0.4	Short	AD-FC	$6,640	$29,740	$-33,210	0.83	12	$62,950	0.44
1	0.8	Long	B-CL	$1,751	$3,930	$-1,950	0.91	11	$5,190	1.25
1.4	1.2	Short	B-CL	$1,475	$6,540	$-2,560	0.69	13	$9,080	0.49
0.2	1.4	Long	B-HO	$29,759	$119,643	$-20,708	0.73	11	$74,704	0.74
0.6	0.6	Short	B-HO	$9,792	$28,245	$-13,610	0.77	13	$49,857	0.82
1.2	0.2	Long	B-KW	$57,633	$153,770	$-24,840	0.91	11	$387,410	1.1
0.2	1.4	Short	B-KW	$46,193	$687,640	$-78,460	0.27	11	$737,580	0.21
0.2	1.4	Long	B-NG	$12,464	$304,740	$-58,960	0.14	14	$309,200	0.11
0.2	0.8	Short	B-NG	$1,764	$119,090	$-22,210	0.17	12	$141,300	0.04
1.2	0.8	Long	B-PL	$8,029	$21,845	$-12,435	0.91	11	$33,395	1.02
1.2	0.6	Short	B-PL	$4,944	$42,280	$-13,620	0.75	12	$44,050	0.33
0.6	0.2	Long	B-W	$35,165	$172,685	$-75,165	0.92	12	$218,085	0.59
0.2	1	Short	B-W	$21,007	$390,010	$-43,215	0.31	13	$421,850	0.18
1.2	0.6	Long	BO-C	$9,178	$18,480	$-1,150	0.91	11	$32,130	1.72
1.2	1	Short	BO-C	$8,944	$45,540	$-21,370	0.83	12	$55,120	0.52
0.8	1	Long	BO-KW	$9,582	$66,834	$-23,428	0.67	12	$70,836	0.35
1.2	0.4	Short	BO-KW	$4,206	$17,018	$-25,498	0.75	12	$40,546	0.34
0.8	0.8	Long	BO-RR	$2,218	$8,376	$-3,780	0.73	11	$11,256	0.54
0.2	1.4	Short	BO-RR	$1,195	$8,280	$-1,838	0.29	14	$10,118	0.33
0.4	1.4	Long	BO-W	$8,303	$59,758	$-13,750	0.46	13	$61,774	0.33
1.2	0.6	Short	BO-W	$6,973	$23,978	$-26,540	0.82	11	$45,298	0.55
1.4	0.4	Long	BP-NG	$16,160	$144,365	$-72,568	0.77	13	$201,863	0.29
0.8	0.8	Short	BP-NG	$31,446	$113,580	$-36,638	0.82	11	$150,218	0.78
0.6	0.2	Long	C-KW	$1,138	$89,360	$-24,890	0.55	20	$107,450	0.05
1.4	0.6	Short	C-KW	$7,892	$25,060	$-20,940	0.83	12	$46,235	0.65
1	0.2	Long	C-O	$3,171	$13,725	$-2,850	0.84	19	$24,150	0.87
0.6	0.8	Short	C-O	$5,599	$21,275	$-7,225	0.75	12	$26,613	0.67
1	0.2	Long	C-RS	$1,731	$7,481	$-2,846	0.87	15	$17,972	0.71

0.4	1.2	Short	C-RS	$1,870	$33,921	$-6,797	0.36	11	$40,718	0.16
0.6	0.4	Long	C-W	$1,499	$88,860	$-28,615	0.56	16	$110,550	0.06
0.6	0.8	Short	C-W	$7,693	$24,160	$-15,702	0.73	11	$38,975	0.48
0.8	0.2	Long	CD-FC	$13,519	$52,630	$-18,790	0.89	19	$87,520	0.81
1.2	0.6	Short	CD-FC	$15,604	$79,310	$-9,080	0.75	12	$152,480	0.64
1.4	0.4	Long	CL-G	$8,157	$44,220	$-59,430	0.89	45	$133,530	0.49
1	0.4	Short	CL-G	$6,759	$24,920	$-38,080	0.82	45	$60,600	0.67
1.2	0.8	Long	CL-HO	$19,811	$121,578	$-794	0.83	12	$78,996	0.6
0.4	0.6	Short	CL-HO	$13,715	$53,094	$-3,700	0.89	19	$39,401	1.01
0.6	0.2	Long	CL-KW	$59,623	$237,410	$-136,600	0.92	13	$328,230	0.67
0.2	1.4	Short	CL-KW	$46,320	$673,950	$-68,920	0.27	11	$721,850	0.21
0.4	1.4	Long	CL-NG	$16,013	$314,810	$-59,470	0.18	11	$297,800	0.12
0.6	0.2	Short	CL-NG	$9,180	$86,570	$-63,270	0.64	11	$167,440	0.17
1.4	0.6	Long	CL-PL	$7,064	$23,890	$-14,300	0.92	12	$36,810	0.85
0.8	0.4	Short	CL-PL	$3,903	$40,730	$-9,925	0.72	18	$42,735	0.33
0.2	1.2	Long	CL-RR	$10,993	$101,680	$-34,850	0.42	12	$108,290	0.26
0.4	1	Short	CL-RR	$9,889	$113,020	$-36,450	0.45	11	$135,310	0.21
0.6	0.2	Long	CL-W	$28,984	$152,310	$-80,790	0.94	17	$203,610	0.62
0.2	1.2	Short	CL-W	$25,867	$377,260	$-37,915	0.27	11	$405,925	0.21
0.6	0.2	Long	CT-SI	$228,475	$966,585	$-372,335	0.64	11	$1,338,920	0.55
0.2	0.4	Short	CT-SI	$45,823	$773,780	$-128,035	0.29	14	$1,121,820	0.16
0.6	0.8	Long	FC-LB	$14,091	$54,587	$-13,669	0.75	12	$67,864	0.69
1.2	0.2	Short	FC-LB	$3,177	$15,719	$-26,349	0.83	12	$44,983	0.31
0.2	0.8	Long	FV-SF	$1,512	$20,490	$-3,534	0.23	13	$23,642	0.17
0.2	0.2	Short	FV-SF	$1,842	$26,341	$-3,792	0.42	12	$30,133	0.22
0.2	1.4	Long	FV-TY	$1,079	$6,241	$-1,071	0.36	11	$6,984	0.44
1	0.4	Short	FV-TY	$1,059	$4,304	$-1,946	0.92	12	$6,250	0.75
0.6	1.2	Long	G-HO	$10,230	$32,029	$-6,059	0.85	27	$54,217	1.09
1.4	0.4	Short	G-HO	$5,798	$54,042	$-50,014	0.86	138	$131,955	0.59
0.8	0.2	Long	G-KW	$11,598	$38,178	$-32,773	0.92	12	$66,000	0.65
0.2	1	Short	G-KW	$6,058	$122,490	$-12,898	0.29	14	$132,250	0.17
0.2	1.4	Long	G-NG	$15,339	$343,055	$-48,485	0.14	14	$298,190	0.13
0.2	0.8	Short	G-NG	$555	$95,505	$-20,895	0.17	12	$150,790	0.01
0.2	0.2	Short	HG-OJ	$8,121	$794,488	$-112,488	0.35	20	$882,718	0.04
0.4	0.4	Long	HO-NG	$5,886	$72,322	$-13,731	0.42	12	$77,383	0.21
0.2	1	Short	HO-NG	$343	$60,007	$-8,670	0.13	15	$66,730	0.02
0.4	0.8	Long	KC-SI	$20,972	$90,504	$-37,218	0.58	12	$127,721	0.43
1.2	0.2	Short	KC-SI	$22,313	$107,861	$-3,990	0.94	18	$188,618	0.93
0.6	0.6	Long	KW-O	$15,922	$51,953	$-24,773	0.83	12	$93,203	0.68
0.4	0.6	Short	KW-O	$9,488	$205,615	$-51,110	0.5	16	$236,788	0.15
1	0.4	Long	KW-RR	$9,029	$44,683	$-31,735	0.83	18	$73,545	0.45
1.2	0.6	Short	KW-RR	$6,450	$113,780	$-40,920	0.62	13	$146,845	0.15
0.2	0.2	Long	KW-RS	$12,566	$66,653	$-28,757	0.73	11	$149,605	0.51
1.4	0.4	Short	KW-RS	$15,345	$223,181	$-169,057	0.75	12	$362,087	0.13
0.2	1	Long	KW-S	$7,364	$43,240	$-5,585	0.42	12	$47,938	0.43
0.8	0.4	Short	KW-S	$7,788	$38,765	$-17,298	0.83	12	$60,010	0.6

0.2	0.2	Long	LB-NE	$-1,398	$32,186	$-6,136	0.15	13	$63,773	-0.13
0.6	0.2	Short	LB-NE	$4,360	$28,416	$-15,480	0.83	12	$43,896	0.37
0.8	0.6	Long	LB-NG	$21,199	$149,397	$-51,804	0.67	12	$152,195	0.34
0.8	0.6	Short	LB-NG	$30,556	$91,158	$-38,891	0.91	11	$127,527	0.87
0.4	0.4	Long	O-W	$1,452	$41,090	$-8,360	0.58	19	$49,760	0.12
0.4	0.8	Short	O-W	$5,453	$16,865	$-6,460	0.73	11	$24,523	0.7
1	0.4	Long	PL-W	$35,755	$269,150	$-166,035	0.92	12	$501,835	0.38
0.2	1.2	Short	PL-W	$7,153	$204,235	$-59,245	0.31	13	$254,295	0.09
0.6	1	Long	RR-S	$5,130	$30,675	$-14,030	0.55	11	$43,045	0.29
1.2	0.4	Short	RR-S	$6,465	$21,840	$-24,940	0.87	15	$46,780	0.62
0.6	1	Long	RR-SM	$12,160	$43,800	$-13,250	0.58	12	$53,830	0.56
0.4	1.4	Short	RR-SM	$9,250	$72,620	$-10,050	0.33	12	$82,440	0.32
0.4	1.2	Long	RR-W	$5,868	$85,780	$-21,700	0.27	11	$95,920	0.18
1.2	0.6	Short	RR-W	$7,373	$38,540	$-27,110	0.82	11	$68,860	0.38
0.2	1.4	Long	RS-W	$7,186	$94,768	$-16,184	0.25	12	$91,082	0.2
0.2	0.4	Short	RS-W	$9,199	$29,264	$-8,684	0.67	12	$38,880	0.67
0.8	0.4	Long	S-W	$31,824	$137,130	$-17,520	0.92	13	$186,625	0.89
0.4	1	Short	S-W	$21,570	$148,693	$-32,445	0.5	12	$181,138	0.34
0.2	0.2	Long	SF-TU	$-402	$19,134	$-3,910	0.17	12	$21,144	-0.06
0.2	0.2	Short	SF-TU	$-679	$12,465	$-4,054	0.33	12	$30,156	-0.14
0.6	0.2	Long	SF-TY	$2,687	$17,051	$-7,357	0.82	11	$21,410	0.42
0.2	1	Short	SF-TY	$2,209	$21,907	$-4,862	0.25	12	$26,769	0.22
0.6	0.4	Long	TU-TY	$874	$8,174	$-5,138	0.55	11	$13,435	0.21
0.6	0.4	Short	TU-TY	$-429	$3,752	$-6,185	0.55	11	$9,966	-0.13
0.4	0.6	Long	CL-RB	$8,423	$85,588	$-25,816	0.43	14	$95,821	0.22
1.2	0.4	Short	CL-RB	$13,316	$36,599	$-58,066	0.86	14	$124,171	0.56
0.4	1.2	Long	G-RB	$19,840	$70,209	$-22,040	0.54	13	$90,385	0.51
1.4	0.4	Short	G-RB	$12,262	$44,712	$-67,462	0.86	14	$112,175	0.34
1.2	0.6	Long	HG-RB	$39,271	$219,010	$-92,986	0.92	13	$285,289	0.6
1.2	0.2	Short	HG-RB	$24,209	$107,574	$-81,561	0.94	18	$180,504	0.66
1	0.6	Long	HO-RB	$5,893	$17,583	$-8,797	0.77	13	$26,195	0.64
1.2	0.2	Short	HO-RB	$4,157	$18,226	$-11,078	0.83	12	$28,791	0.47
0.4	1	Long	KW-RB	$37,288	$141,352	$-38,988	0.67	12	$156,320	0.59
0.2	1	Short	KW-RB	$41,027	$195,510	$-24,876	0.36	11	$220,386	0.43
0.2	0.2	Long	NG-RB	$-6,706	$36,299	$-20,491	0.23	13	$87,570	-0.4
1.4	0.6	Long	O-RB	$24,869	$56,962	$-10,218	0.8	15	$166,667	1.23
0.4	0.8	Short	O-RB	$42,383	$188,240	$-46,549	0.69	13	$196,789	0.55
0.2	1.2	Long	PA-RB	$10,184	$123,925	$-14,693	0.25	12	$94,749	0.24
0.6	0.2	Short	PA-RB	$5,539	$84,001	$-22,444	0.58	12	$112,221	0.19
1	0.4	Long	PL-RB	$36,484	$193,417	$-67,665	0.83	12	$261,082	0.6
1.4	0.2	Short	PL-RB	$32,888	$98,945	$-15,428	0.94	17	$159,393	1.18
0.4	0.2	Long	RB-RR	$35,835	$407,521	$-98,576	0.67	18	$463,877	0.28
0.4	1	Short	RB-RR	$77,165	$269,350	$-72,348	0.55	11	$316,774	0.53
1	0.2	Long	RB-S	$44,118	$237,896	$-126,749	0.87	15	$302,575	0.55
0.2	1.4	Short	RB-S	$72,411	$286,236	$-37,667	0.45	11	$318,297	0.56
1	0.2	Long	RB-SM	$21,963	$119,189	$-72,130	0.91	11	$171,640	0.48

0.6	0.8	Short	RB-SM	$20,818	$216,175	$-51,016	0.54	13	$255,801	0.27
0.6	0.2	Long	RB-W	$26,074	$125,396	$-53,097	0.73	11	$163,598	0.43
0.2	1	Short	RB-W	$14,335	$108,779	$-16,931	0.33	15	$121,335	0.31
1.2	0.2	Long	ES-TF	$994	$59,090	$-56,940	0.58	12	$120,600	0.03
0.2	0.2	Short	ES-TF	$-1,074	$35,518	$-12,640	0.33	15	$117,515	-0.07
0.2	0.6	Long	LB-TF	$1,298	$15,441	$-2,698	0.25	12	$18,139	0.21
0.4	0.2	Short	LB-TF	$1,527	$24,446	$-4,447	0.45	11	$28,264	0.18
0.8	0.2	Long	NG-TF	$12,766	$54,775	$-36,810	0.95	20	$82,405	0.79
0.4	1.4	Short	NG-TF	$19,463	$160,430	$-37,710	0.33	12	$171,365	0.27
0.4	0.2	Long	TF-YM	$1,421	$12,580	$-5,390	0.45	11	$30,295	0.23
0.4	0.2	Short	TF-YM	$1,053	$21,655	$-4,880	0.54	13	$29,055	0.15

Table 8: Filter trading results on in sample data

PT	SL	SD	L/S	Spread	Avg $	Max Win	Max Loss	Win%	#	DD	Sharpe
1.5	0.2	0.6	Long	AD-FC	$18,562	$48,668	$-6,489	0.45	11	$55,157	0.65
1.5	0.2	1.4	Short	AD-FC	$7,280	$48,668	$-6,489	0.25	12	$55,157	0.29
1.5	1.4	0.4	Long	B-CL	$1,897	$2,285	$-2,133	0.92	12	$4,418	1.5
2	1.4	1.2	Short	B-CL	$1,433	$3,047	$-2,133	0.69	13	$5,180	0.58
0.5	0.2	1.4	Long	B-HO	$13,228	$23,084	$-9,234	0.7	23	$32,317	0.87
0.5	1.2	0.2	Short	B-HO	$16,523	$23,084	$-55,401	0.92	12	$78,485	0.73
0.5	0.4	0.2	Long	B-KW	$69,926	$103,974	$-83,179	0.82	11	$187,153	0.92
1	0.2	1.2	Short	B-KW	$29,687	$207,948	$-41,590	0.29	14	$249,537	0.25
0.5	1.4	1.2	Long	B-NG	$27,971	$42,765	$-119,741	0.91	11	$162,505	0.57
0.5	1.2	0.8	Short	B-NG	$16,308	$42,765	$-102,635	0.82	11	$145,399	0.28
0.5	1.2	0.8	Long	B-PL	$3,914	$4,918	$-11,802	0.94	17	$16,720	0.97
1.5	0.8	0.4	Short	B-PL	$6,032	$14,753	$-7,868	0.62	13	$22,621	0.53
0.5	0.2	0.8	Long	B-W	$36,305	$58,762	$-23,505	0.73	11	$82,266	0.95
0.5	0.2	1.4	Short	B-W	$8,116	$58,762	$-23,505	0.38	13	$82,266	0.2
0.5	0.4	1.4	Long	BO-C	$6,098	$8,050	$-6,440	0.87	15	$14,490	1.2
1	0.8	1.2	Short	BO-C	$8,176	$16,100	$-12,880	0.73	11	$28,980	0.61
1.5	0.2	1.4	Long	BO-KW	$7,389	$30,310	$-4,041	0.33	18	$34,352	0.44
1	0.4	1.4	Short	BO-KW	$7,328	$20,207	$-8,083	0.55	11	$28,290	0.5
1	1.2	0.6	Long	BO-RR	$1,965	$3,309	$-3,971	0.82	11	$7,280	0.67
1	1.2	1	Long	BO-RR	$1,965	$3,309	$-3,971	0.82	11	$7,280	0.67
0.5	1.4	1	Short	BO-RR	$1,151	$1,655	$-4,633	0.92	13	$6,287	0.67
1.5	1	1.4	Long	BO-W	$13,067	$29,447	$-19,631	0.67	12	$49,078	0.54
0.5	1	0.8	Short	BO-W	$7,342	$9,816	$-19,631	0.92	12	$29,447	0.87
1.5	1.4	0.4	Long	BP-NG	$27,926	$54,090	$-50,484	0.75	12	$104,574	0.59
1	0.8	1	Short	BP-NG	$25,222	$36,060	$-28,848	0.83	12	$64,908	1
1.5	0.2	0.2	Long	C-KW	$5,011	$36,282	$-4,838	0.24	25	$41,120	0.28
0.5	0.2	1.2	Short	C-KW	$4,378	$12,094	$-4,838	0.55	11	$16,932	0.5
1	0.8	0.6	Long	C-O	$9,004	$10,790	$-8,632	0.91	11	$18,915	1.54
0.5	0.6	1.2	Short	C-O	$4,296	$5,395	$-6,474	0.91	11	$11,869	1.21

0.5	0.6	0.2	Long	C-RS	$2,920	$4,900	$-5,880	0.82	11	$10,780	0.67
0.5	1	1.2	Short	C-RS	$2,207	$4,900	$-9,800	0.82	11	$14,700	0.37
0.5	1	1.4	Short	C-RS	$2,207	$4,900	$-9,800	0.82	11	$14,700	0.37
1.5	0.2	0.8	Long	C-W	$5,349	$35,795	$-4,773	0.25	24	$40,567	0.3
0.5	0.8	0.8	Short	C-W	$9,091	$11,932	$-19,090	0.91	11	$31,022	0.97
0.5	0.2	0.8	Long	CD-FC	$22,606	$34,809	$-13,924	0.75	12	$48,733	1.03
0.5	0.2	1.2	Short	CD-FC	$16,046	$34,809	$-13,924	0.62	13	$48,733	0.65
0.5	0.2	1.4	Short	CD-FC	$16,046	$34,809	$-13,924	0.62	13	$48,733	0.65
0.5	1.4	0.2	Long	CL-G	$10,107	$18,616	$-52,125	0.88	25	$70,742	0.43
0.5	1.4	0.4	Long	CL-G	$10,107	$18,616	$-52,125	0.88	25	$70,742	0.43
0.5	0.6	1	Short	CL-G	$9,145	$18,616	$-22,339	0.77	13	$40,956	0.51
0.5	1	1.2	Long	CL-HO	$17,764	$23,712	$-47,424	0.92	12	$71,136	0.87
0.5	0.6	0.4	Short	CL-HO	$19,679	$23,712	$-28,454	0.92	13	$52,166	1.36
0.5	0.6	0.6	Short	CL-HO	$19,679	$23,712	$-28,454	0.92	13	$52,166	1.36
0.5	0.6	0.6	Long	CL-KW	$81,420	$101,800	$-122,160	0.91	11	$223,961	1.21
0.5	0.6	0.8	Long	CL-KW	$81,420	$101,800	$-122,160	0.91	11	$223,961	1.21
1	0.2	1.4	Short	CL-KW	$40,700	$203,600	$-40,720	0.33	12	$244,321	0.34
1	0.6	1.2	Long	CL-NG	$32,071	$83,438	$-50,063	0.62	13	$133,500	0.47
0.5	1	1	Short	CL-NG	$18,943	$41,719	$-83,438	0.82	11	$125,156	0.37
0.5	1.2	0.8	Long	CL-PL	$4,027	$4,876	$-11,703	0.95	20	$16,580	1.09
2	0.8	0.6	Short	CL-PL	$8,107	$19,506	$-7,802	0.58	12	$27,308	0.58
0.5	0.6	1	Long	CL-RR	$17,461	$35,509	$-42,610	0.77	13	$78,119	0.51
0.5	0.2	1	Short	CL-RR	$1,475	$35,509	$-14,203	0.32	19	$49,712	0.06
0.5	0.4	0.8	Long	CL-W	$40,267	$57,553	$-46,042	0.83	12	$103,595	1
1	0.2	1.2	Short	CL-W	$23,001	$115,105	$-23,021	0.33	12	$138,126	0.34
0.5	0.4	1	Long	CT-SI	$137,559	$196,542	$-157,233	0.83	12	$353,775	1
0.5	0.8	1	Short	CT-SI	$76,284	$196,542	$-314,467	0.76	17	$511,009	0.34
0.5	0.8	0.8	Long	FC-LB	$8,695	$10,542	$-16,867	0.93	15	$27,409	1.23
0.5	0.4	1.4	Short	FC-LB	$7,072	$10,542	$-8,434	0.82	11	$18,976	0.92
0.5	0.2	1	Long	FV-SF	$1,147	$6,365	$-2,546	0.42	12	$8,911	0.25
1	0.2	0.2	Short	FV-SF	$3,799	$12,730	$-2,546	0.42	12	$15,275	0.49
0.5	1.2	1	Long	FV-TY	$596	$834	$-2,002	0.92	13	$2,836	0.78
1	1	0.6	Short	FV-TY	$1,345	$1,668	$-1,668	0.91	11	$3,337	1.36
0.5	0.4	1.2	Long	G-HO	$6,855	$26,562	$-21,250	0.59	17	$47,812	0.28
1	0.4	1.4	Short	G-HO	$22,115	$53,125	$-21,250	0.58	12	$74,375	0.58
0.5	0.4	0.4	Long	G-KW	$10,979	$19,998	$-15,998	0.75	12	$35,996	0.68
0.5	0.2	1.4	Short	G-KW	$5,979	$19,998	$-7,999	0.5	16	$27,997	0.41
1	0.6	1.2	Long	G-NG	$30,181	$78,523	$-47,114	0.62	13	$125,637	0.47
0.5	1.2	0.8	Short	G-NG	$14,971	$39,262	$-94,228	0.82	11	$133,490	0.28
0.5	0.2	0.2	Long	HG-OJ	$87,128	$177,524	$-71,010	0.64	11	$248,533	0.7
0.5	0.2	1.4	Short	HG-OJ	$53,237	$177,524	$-71,010	0.5	12	$248,533	0.41
1	0.4	1.4	Long	HO-NG	$9,158	$25,239	$-10,095	0.55	11	$35,334	0.5
0.5	0.2	1.4	Short	HO-NG	$2,504	$12,619	$-5,048	0.43	21	$17,667	0.28
0.5	0.2	1.4	Long	KC-SI	$14,456	$37,359	$-14,943	0.56	16	$52,302	0.54
0.5	1	0.2	Short	KC-SI	$30,334	$37,359	$-74,717	0.94	16	$112,076	1.08
0.5	0.2	1.2	Long	KW-O	$19,389	$36,392	$-14,557	0.67	12	$50,949	0.77

0.5	0.2	1	Short	KW-O	$5,145	$36,392	$-14,557	0.39	31	$50,949	0.2
2	0.2	1.4	Long	KW-RR	$16,144	$53,879	$-5,388	0.36	11	$59,266	0.54
2	0.2	0.8	Short	KW-RR	$6,445	$53,879	$-5,388	0.2	25	$59,266	0.27
0.5	0.2	0.2	Long	KW-RS	$14,407	$58,608	$-23,443	0.46	13	$82,051	0.34
1.5	0.2	1.4	Short	KW-RS	$16,390	$175,824	$-23,443	0.2	15	$199,267	0.2
0.5	0.4	1.4	Long	KW-S	$4,682	$9,681	$-7,745	0.71	14	$17,425	0.58
0.5	0.6	1	Short	KW-S	$8,022	$9,681	$-11,617	0.92	13	$21,298	1.36
0.5	0.4	1	Long	LB-NE	$1,874	$11,837	$-9,470	0.53	15	$21,307	0.17
0.5	0.6	0.2	Short	LB-NE	$4,715	$11,837	$-14,205	0.73	11	$26,042	0.39
1.5	0.6	0.6	Long	LB-NG	$21,317	$71,125	$-28,450	0.5	14	$99,574	0.41
0.5	0.6	1	Short	LB-NG	$18,947	$23,708	$-28,450	0.91	11	$52,158	1.21
1	0.4	1.2	Long	O-W	$3,118	$15,688	$-6,275	0.43	14	$21,963	0.28
1	0.4	1.4	Long	O-W	$3,118	$15,688	$-6,275	0.43	14	$21,963	0.28
0.5	0.4	1	Short	O-W	$5,471	$7,844	$-6,275	0.83	12	$14,119	1
0.5	0.4	1.2	Short	O-W	$5,471	$7,844	$-6,275	0.83	12	$14,119	1
0.5	1	0.2	Long	PL-W	$57,869	$79,597	$-159,194	0.91	11	$238,791	0.8
0.5	0.2	1.4	Short	PL-W	$5,286	$79,597	$-31,839	0.33	12	$111,436	0.1
1	0.2	1	Long	RR-S	$1,973	$19,934	$-3,987	0.25	20	$23,920	0.19
0.5	1.2	0.4	Short	RR-S	$7,526	$9,967	$-23,920	0.93	14	$33,887	0.83
1	1.4	1	Long	RR-SM	$8,028	$14,278	$-19,989	0.82	11	$34,267	0.58
1.5	1.4	0.2	Short	RR-SM	$11,046	$21,417	$-19,989	0.75	16	$41,407	0.6
2	0.6	1	Long	RR-W	$8,710	$43,652	$-13,096	0.38	13	$56,747	0.3
1.5	0.8	0.4	Short	RR-W	$14,464	$32,739	$-17,461	0.64	11	$50,199	0.57
1.5	0.2	1.4	Long	RS-W	$8,111	$54,209	$-7,228	0.25	12	$54,753	0.29
0.5	0.6	0.2	Short	RS-W	$10,822	$18,070	$-21,684	0.82	11	$39,754	0.67
0.5	0.6	0.6	Long	S-W	$26,075	$31,953	$-38,344	0.92	12	$70,297	1.29
1	0.6	1.2	Short	S-W	$17,409	$63,906	$-38,344	0.55	11	$102,250	0.33
1.5	0.2	0.2	Long	SF-TU	$1,072	$19,650	$-2,620	0.17	12	$21,281	0.13
0.5	0.8	0.8	Short	SF-TU	$2,272	$6,550	$-10,480	0.75	12	$17,030	0.3
0.5	0.6	0.2	Long	SF-TY	$2,623	$5,874	$-7,049	0.75	12	$12,923	0.45
0.5	0.6	0.8	Short	SF-TY	$1,878	$5,874	$-7,049	0.69	13	$12,923	0.31
0.5	0.6	0.6	Long	TU-TY	$1,405	$3,167	$-3,801	0.75	12	$6,968	0.45
1	0.2	0.4	Short	TU-TY	$233	$6,334	$-1,267	0.2	15	$7,601	0.08
0.5	0.4	1.4	Long	CL-RB	$13,750	$23,553	$-18,843	0.77	13	$42,396	0.74
2	0.4	0.6	Short	CL-RB	$28,244	$94,213	$-18,843	0.42	12	$113,055	0.49
2	0.4	0.8	Short	CL-RB	$28,244	$94,213	$-18,843	0.42	12	$113,055	0.49
1	0.4	1.2	Long	G-RB	$17,218	$43,096	$-17,238	0.57	14	$60,335	0.56
1.5	1.4	0.2	Short	G-RB	$33,380	$64,644	$-60,335	0.75	12	$124,979	0.59
0.5	1	0.8	Long	HG-RB	$26,604	$32,769	$-65,537	0.94	16	$98,306	1.08
1	1.4	0.2	Short	HG-RB	$51,218	$65,537	$-91,752	0.91	11	$157,289	1.08
0.5	1	1.2	Long	HO-RB	$3,177	$4,263	$-8,526	0.92	12	$12,788	0.87
0.5	1	1.4	Short	HO-RB	$3,259	$4,263	$-8,526	0.92	13	$12,788	0.92
0.5	1	1	Long	KW-RB	$32,329	$44,480	$-88,959	0.91	11	$133,439	0.8
0.5	0.6	1	Short	KW-RB	$36,305	$44,480	$-53,376	0.92	12	$97,855	1.29
1	0.2	1	Long	NG-RB	$5,718	$57,379	$-11,476	0.25	12	$68,855	0.18
0.5	0.6	1	Short	NG-RB	$14,104	$28,689	$-34,427	0.77	13	$63,117	0.51

0.5	0.6	1	Long	O-RB	$20,528	$45,661	$-54,793	0.75	12	$100,454	0.45
0.5	1.2	0.8	Short	O-RB	$35,938	$45,661	$-109,587	0.94	16	$155,248	0.93
0.5	0.6	1.4	Long	PA-RB	$10,907	$17,252	$-20,703	0.83	12	$37,955	0.74
0.5	0.4	1.2	Short	PA-RB	$8,763	$17,252	$-13,802	0.73	11	$31,054	0.61
0.5	1.4	0.2	Long	PL-RB	$25,139	$33,695	$-94,347	0.93	15	$128,042	0.76
0.5	0.6	1.4	Short	PL-RB	$26,936	$33,695	$-40,434	0.91	11	$74,130	1.21
1	0.4	0.2	Long	RB-RR	$61,133	$157,815	$-63,126	0.56	16	$220,941	0.54
0.5	1	0.8	Short	RB-RR	$57,367	$78,907	$-157,815	0.91	11	$229,713	0.8
0.5	0.8	0.8	Long	RB-S	$48,830	$62,361	$-99,778	0.92	12	$162,139	1.04
0.5	0.4	1.4	Short	RB-S	$34,279	$62,361	$-49,889	0.75	12	$112,250	0.68
0.5	1	0.2	Long	RB-SM	$23,661	$32,562	$-65,123	0.91	11	$97,685	0.8
0.5	0.6	1	Short	RB-SM	$11,472	$32,562	$-39,074	0.71	17	$71,636	0.34
0.5	1	0.8	Long	RB-W	$23,977	$32,996	$-65,992	0.91	11	$98,987	0.8
0.5	1	1.2	Short	RB-W	$24,727	$32,996	$-65,992	0.92	12	$98,987	0.87
0.5	0.2	0.8	Long	ES-TF	$5,290	$21,574	$-8,629	0.46	13	$30,203	0.34
1	0.4	0.2	Short	ES-TF	$6,212	$43,147	$-17,259	0.39	18	$60,406	0.21
0.5	0.2	1.2	Long	LB-TF	$2,814	$4,361	$-1,744	0.75	12	$6,105	1.03
0.5	0.4	1.4	Short	LB-TF	$2,200	$4,361	$-3,489	0.73	11	$7,849	0.61
0.5	0.6	0.4	Long	NG-TF	$14,090	$22,279	$-26,735	0.83	12	$49,015	0.74
1	0.8	0.8	Short	NG-TF	$12,457	$44,559	$-35,647	0.6	15	$80,206	0.31
1	0.8	1	Short	NG-TF	$12,457	$44,559	$-35,647	0.6	15	$80,206	0.31
0.5	0.6	0.4	Long	TF-YM	$1,604	$4,777	$-5,732	0.7	20	$10,509	0.33
0.5	0.4	0.6	Short	TF-YM	$2,111	$4,777	$-3,821	0.69	13	$8,598	0.52

Table 9: RSI trading results on in sample data

PT	SL	SD	L/S	Spread	Avg $	Max Win	Max Loss	Win%	#	DD	Sharpe
1.5	0.2	0.4	Long	AD-FC	$13,165	$51,910	$-8,980	0.36	11	$58,240	0.45
1.5	0.2	0.6	Long	AD-FC	$13,165	$51,910	$-8,980	0.36	11	$58,240	0.45
2	0.2	0.6	Short	AD-FC	$-1,103	$71,110	$-8,740	0.08	12	$79,410	-0.05
1.5	1.2	0.2	Long	B-CL	$1,590	$2,720	$-2,070	0.82	11	$4,340	0.89
0.5	0.2	1	Short	B-CL	$318	$1,270	$-1,110	0.64	11	$2,380	0.39
0.5	0.2	0.6	Long	B-HO	$694	$30,584	$-19,562	0.36	14	$49,562	0.04
0.5	0.2	0.8	Short	B-KW	$-11,141	$114,400	$-83,670	0.27	11	$198,070	-0.14
0.5	0.4	0.8	Long	B-NG	$-2,969	$64,490	$-65,700	0.45	11	$114,820	-0.06
0.5	0.2	0.2	Short	B-NG	$829	$58,600	$-30,220	0.31	13	$88,820	0.02
0.5	1.4	0.4	Long	B-PL	$6,008	$9,520	$0	1	11	$17,820	4.49
0.5	0.2	0.4	Short	B-PL	$375	$7,380	$-3,920	0.36	11	$10,005	0.09
0.5	0.2	0.8	Short	B-W	$-6,144	$65,585	$-47,190	0.27	11	$112,775	-0.14
0.5	1	0.2	Long	BO-C	$6,973	$15,480	$-16,770	0.91	11	$32,250	0.86
0.5	0.4	0.6	Short	BO-C	$4,987	$15,140	$-7,930	0.73	11	$23,070	0.62
0.5	0.6	1	Long	BO-KW	$6,865	$15,920	$-15,598	0.82	11	$28,300	0.63
1	0.2	0.2	Short	BO-KW	$3,256	$21,140	$-7,046	0.33	12	$28,186	0.26
0.5	0.8	0.4	Long	BO-RR	$1,175	$2,528	$-3,584	0.85	13	$5,848	0.61

2	0.2	1	Short	BO-RR	$1,164	$6,922	$-1,206	0.27	11	$8,128	0.33
0.5	0.2	1.2	Long	BO-W	$6,704	$22,120	$-9,536	0.64	11	$21,434	0.63
0.5	0.4	0.2	Short	BO-W	$7,710	$14,754	$-11,994	0.83	12	$23,602	0.9
1.5	1	0.2	Long	BP-NG	$-4,374	$61,210	$-45,233	0.36	11	$102,384	-0.09
2	0.2	0.8	Short	BP-NG	$15,378	$88,740	$-11,262	0.27	11	$98,416	0.37
1	0.2	0.8	Long	C-KW	$6,852	$28,048	$-15,190	0.45	11	$43,238	0.38
0.5	0.4	0.4	Short	C-KW	$7,473	$19,135	$-11,690	0.73	11	$27,000	0.63
0.5	0.4	0.4	Long	C-O	$3,507	$7,750	$-5,488	0.75	12	$12,262	0.69
0.5	0.6	0.2	Short	C-O	$2,107	$6,750	$-8,825	0.73	11	$14,588	0.34
0.5	0.6	0.2	Short	C-RS	$-256	$6,471	$-7,474	0.55	11	$13,575	-0.04
0.5	0.2	0.4	Long	C-W	$1,960	$19,473	$-7,978	0.4	15	$21,113	0.19
0.5	0.2	0.6	Short	CD-FC	$12,459	$38,390	$-19,500	0.55	11	$57,160	0.44
0.5	0.2	0.4	Long	CL-HO	$1,676	$29,574	$-18,619	0.38	13	$48,193	0.08
0.5	0.2	0.2	Short	CL-KW	$-15,671	$118,950	$-80,560	0.2	15	$189,390	-0.24
0.5	1	0.2	Long	CL-NG	$-9,783	$63,560	$-125,420	0.64	11	$175,340	-0.12
1.5	0.2	0.2	Short	CL-NG	$7,182	$129,690	$-24,720	0.18	11	$154,410	0.12
0.5	1	0.4	Long	CL-PL	$6,094	$10,600	$0	1	11	$18,015	3.83
1	0.4	0.2	Short	CL-PL	$963	$11,580	$-6,230	0.36	11	$17,810	0.13
0.5	0.2	0.6	Short	CL-RR	$-2,096	$37,100	$-28,910	0.29	14	$65,680	-0.08
0.5	0.2	0.6	Short	CL-W	$-12,549	$65,685	$-44,190	0.18	11	$105,675	-0.33
1.5	0.4	0.2	Short	CT-SI	$38,298	$685,280	$-259,690	0.27	11	$892,870	0.1
0.5	0.6	0.2	Long	FC-LB	$4,252	$11,432	$-14,246	0.73	11	$25,678	0.37
0.5	0.6	0.2	Short	FC-LB	$5,090	$14,682	$-13,998	0.73	11	$28,681	0.42
1	0.2	0.6	Long	FV-SF	$-16	$14,426	$-4,046	0.18	11	$18,472	0
0.5	0.2	0.4	Long	FV-TY	$446	$976	$-899	0.69	13	$1,867	0.66
0.5	0.4	0.2	Short	FV-TY	$541	$1,179	$-1,181	0.82	11	$2,117	0.73
0.5	0.4	0.2	Short	G-KW	$1,725	$22,665	$-20,335	0.5	12	$42,163	0.09
0.5	0.8	0.8	Long	G-NG	$10,490	$54,560	$-89,725	0.73	11	$133,150	0.18
0.5	0.2	0.2	Short	HG-OJ	$4,575	$225,398	$-91,280	0.31	13	$316,678	0.03
0.5	0.2	0.4	Short	HG-OJ	$4,575	$225,398	$-91,280	0.31	13	$316,678	0.03
0.5	0.2	0.6	Short	HG-OJ	$4,575	$225,398	$-91,280	0.31	13	$316,678	0.03
2	0.4	0.2	Long	HO-NG	$-1,742	$51,260	$-18,339	0.18	11	$51,243	-0.07
0.5	0.2	0.2	Short	HO-NG	$754	$16,863	$-7,605	0.33	15	$24,469	0.08
0.5	0.2	0.8	Short	KW-O	$2,520	$39,465	$-44,773	0.42	12	$84,238	0.08
0.5	0.8	0.2	Long	KW-RR	$5,381	$22,845	$-25,558	0.75	12	$48,403	0.3
0.5	1	0.4	Short	KW-RR	$8,890	$21,670	$-28,635	0.85	13	$45,075	0.53
0.5	0.2	0.6	Short	KW-RS	$-14,953	$67,642	$-63,041	0.18	17	$130,682	-0.38
2	0.2	0.8	Long	KW-S	$3,196	$41,078	$-6,548	0.18	11	$46,475	0.18
0.5	0.2	0.2	Short	KW-S	$2,070	$12,340	$-5,610	0.45	11	$16,338	0.26
0.5	0.2	0.2	Long	LB-NE	$85	$13,101	$-6,521	0.31	13	$19,622	0.01
0.5	0.2	0.8	Short	LB-NE	$2,156	$13,635	$-7,187	0.42	12	$20,822	0.23
1.5	0.6	0.4	Long	LB-NG	$4,404	$73,500	$-53,905	0.36	11	$127,405	0.08
1	0.2	0.2	Short	LB-NG	$10,129	$48,274	$-13,810	0.36	11	$62,084	0.34
0.5	0.2	0.4	Long	O-W	$2,634	$9,915	$-5,072	0.53	15	$13,150	0.41
0.5	0.2	0.8	Short	PL-W	$7,820	$98,165	$-46,785	0.36	11	$133,345	0.13
1	0.2	1	Long	RR-S	$2,599	$22,240	$-4,485	0.27	11	$26,725	0.22

2	0.2	0.2	Short	RR-S	$6,346	$40,315	$-9,270	0.27	11	$49,475	0.29
0.5	0.6	0.6	Long	RR-SM	$2,168	$10,100	$-10,940	0.67	12	$21,040	0.25
2	0.4	0.2	Short	RR-SM	$8,427	$31,300	$-8,480	0.42	12	$38,920	0.44
0.5	1.2	0.2	Long	RR-W	$5,714	$23,260	$-28,430	0.82	11	$39,980	0.33
0.5	1.2	0.4	Short	RR-W	$7,997	$13,390	$-32,950	0.91	11	$46,340	0.59
0.5	0.2	0.6	Long	RS-W	$3,969	$19,700	$-10,722	0.45	11	$30,086	0.28
0.5	0.2	0.2	Long	S-W	$15,875	$35,330	$-18,120	0.64	11	$52,350	0.64
0.5	0.6	0.4	Short	S-W	$8,012	$50,105	$-48,095	0.64	11	$98,200	0.2
0.5	0.2	0.4	Short	SF-TU	$-943	$6,915	$-4,035	0.21	14	$10,950	-0.22
0.5	0.6	0.2	Short	SF-TY	$-230	$6,319	$-9,024	0.55	11	$15,344	-0.03
0.5	0.2	0.2	Long	TU-TY	$22	$4,065	$-2,216	0.33	12	$5,531	0.02
2	0.2	0.4	Short	TU-TY	$-271	$12,612	$-2,779	0.09	11	$14,016	-0.06
2	0.2	0.6	Short	TU-TY	$-271	$12,612	$-2,779	0.09	11	$14,016	-0.06
1	0.4	0.6	Long	CL-RB	$13,093	$59,890	$-23,709	0.45	11	$79,783	0.33
0.5	1.2	0.2	Short	CL-RB	$19,527	$46,492	$-56,876	0.91	11	$103,368	0.75
0.5	1.2	0.4	Short	CL-RB	$19,527	$46,492	$-56,876	0.91	11	$103,368	0.75
1	0.6	0.2	Long	G-RB	$5,479	$55,031	$-34,503	0.45	11	$89,534	0.13
2	0.2	0.2	Short	G-RB	$1,524	$86,525	$-23,789	0.15	13	$110,314	0.04
0.5	0.6	0.2	Long	HG-RB	$10,348	$45,240	$-42,440	0.64	11	$87,680	0.25
1.5	1.2	0.2	Long	HO-RB	$7,247	$16,659	$-11,414	0.73	11	$28,073	0.62
1	0.4	0.6	Short	HO-RB	$4,674	$12,199	$-5,319	0.67	12	$17,518	0.68
0.5	0.4	0.6	Long	KW-RB	$10,131	$56,667	$-39,325	0.55	11	$92,606	0.22
1.5	0.2	0.4	Short	KW-RB	$37,236	$151,210	$-31,182	0.36	11	$166,460	0.45
0.5	0.2	0.2	Long	NG-RB	$-1,969	$35,564	$-21,170	0.27	11	$52,761	-0.09
1	0.2	0.2	Short	NG-RB	$5,308	$59,861	$-19,650	0.27	11	$73,924	0.15
0.5	0.8	0.2	Long	O-RB	$39,532	$59,548	$-74,661	0.91	11	$134,209	1.04
2	0.2	0.2	Short	O-RB	$33,568	$189,920	$-33,132	0.27	11	$223,051	0.34
2	0.4	0.2	Long	PA-RB	$-3,347	$73,400	$-27,062	0.17	12	$97,172	-0.09
1.5	0.2	0.2	Short	PL-RB	$33,946	$110,370	$-23,545	0.42	12	$133,916	0.54
0.5	0.4	0.8	Short	RB-RR	$34,833	$104,754	$-70,917	0.64	11	$175,670	0.43
1.5	0.4	0.6	Short	RB-S	$34,241	$200,962	$-66,746	0.36	11	$254,750	0.27
1.5	0.4	1	Short	RB-SM	$17,557	$113,798	$-38,345	0.36	11	$145,502	0.26
1.5	0.2	0.2	Long	RB-W	$22,497	$100,404	$-22,616	0.33	12	$123,020	0.39
0.5	0.6	0.8	Short	RB-W	$22,076	$41,970	$-43,624	0.82	11	$83,569	0.68
0.5	0.4	1	Short	LB-TF	$1,150	$5,551	$-4,192	0.58	12	$9,478	0.26
0.5	0.8	0.6	Short	NG-TF	$1,148	$39,345	$-54,295	0.64	11	$78,950	0.03

Table 10: Moving average trading results on in sample data

PT	SL	SD	L/S	Spread	Avg $	Max Win	Max Loss	Win%	#	DD	Sharpe
1.5	0.2	0.6	Long	AD-FC	$10,462	$48,668	$-6,489	0.31	13	$55,157	0.4
1.5	0.2	0.4	Short	AD-FC	$386	$48,668	$-6,489	0.12	24	$55,157	0.02
2	1.2	1	Long	B-CL	$1,697	$3,047	$-1,828	0.73	11	$4,875	0.75
1.5	1.2	1.4	Short	B-CL	$1,143	$2,285	$-1,828	0.73	11	$4,113	0.61

0.5	0.6	0.4	Long	B-HO	$8,554	$23,084	$-27,701	0.71	14	$50,784	0.36
1.5	0.2	0.2	Short	B-HO	$5,840	$69,251	$-9,234	0.19	26	$78,485	0.19
1	0.6	0.2	Long	B-KW	$56,693	$207,948	$-124,769	0.55	11	$332,716	0.33
1	0.2	0.4	Short	B-KW	$-20	$207,948	$-41,590	0.17	12	$249,537	0
0.5	1.4	0.6	Long	B-NG	$29,202	$42,765	$-119,741	0.92	12	$162,505	0.62
1	0.2	0.4	Short	B-NG	$7,311	$85,529	$-17,106	0.24	42	$102,635	0.17
1	1	0.8	Long	B-PL	$2,790	$9,835	$-9,835	0.64	14	$19,671	0.29
0.5	0.2	0.4	Short	B-PL	$621	$4,918	$-1,967	0.38	66	$6,885	0.19
1	0.6	0.2	Long	B-W	$32,032	$117,523	$-70,514	0.55	11	$188,037	0.33
1	0.2	0.4	Short	B-W	$-20	$117,523	$-23,505	0.17	12	$141,028	0
0.5	1.4	0.6	Long	BO-C	$5,249	$8,050	$-22,540	0.91	11	$30,590	0.57
1	0.2	0.6	Short	BO-C	$1,397	$16,100	$-3,220	0.24	25	$19,320	0.17
1.5	0.4	1	Long	BO-KW	$14,293	$30,310	$-8,083	0.58	12	$38,393	0.72
2	0.4	0.2	Short	BO-KW	$8,063	$40,414	$-8,083	0.33	15	$48,496	0.34
2	0.4	1.2	Long	BO-RR	$1,304	$6,618	$-1,324	0.33	12	$7,942	0.34
0.5	0.2	0.8	Short	BO-RR	$443	$1,655	$-662	0.49	35	$2,316	0.39
1.5	0.2	1.2	Long	BO-W	$11,223	$29,447	$-3,926	0.45	11	$33,373	0.65
0.5	1.2	0.2	Short	BO-W	$5,028	$9,816	$-23,557	0.86	21	$33,373	0.42
0.5	1	1	Long	BP-NG	$8,995	$18,030	$-36,060	0.83	12	$54,090	0.43
1	0.2	1	Short	BP-NG	$8,040	$36,060	$-7,212	0.35	17	$43,272	0.38
0.5	0.2	1	Long	C-KW	$3,608	$12,094	$-4,838	0.5	12	$16,932	0.41
1	0.6	0.2	Short	C-KW	$6,306	$24,188	$-14,513	0.54	13	$38,701	0.32
1	1.2	0.2	Long	C-O	$3,466	$10,790	$-12,948	0.69	13	$23,738	0.31
1.5	0.2	0.6	Short	C-O	$1,261	$16,185	$-2,158	0.19	16	$18,343	0.17
1	0.6	0.2	Long	C-RS	$2,653	$9,800	$-5,880	0.55	11	$15,680	0.33
2	0.2	0.6	Short	C-RS	$-440	$19,600	$-1,960	0.07	14	$21,560	-0.07
1.5	0.2	1	Long	C-W	$9,959	$35,795	$-4,773	0.36	11	$40,567	0.49
0.5	0.8	0.2	Short	C-W	$4,156	$11,932	$-19,090	0.75	12	$31,022	0.3
1	0.4	0.2	Long	CD-FC	$25,296	$69,618	$-27,847	0.55	11	$97,465	0.5
0.5	0.2	0.4	Short	CD-FC	$3,256	$34,809	$-13,924	0.35	17	$48,733	0.14
1	1.4	0.2	Long	CL-G	$20,966	$37,232	$-52,125	0.82	11	$89,358	0.58
1	1.4	0.4	Long	CL-G	$20,966	$37,232	$-52,125	0.82	11	$89,358	0.58
0.5	1	0.4	Short	CL-G	$9,778	$18,616	$-37,232	0.84	19	$55,849	0.47
0.5	0.6	0.4	Long	CL-HO	$6,303	$23,712	$-28,454	0.67	12	$52,166	0.25
1.5	0.2	0.2	Short	CL-HO	$8,818	$71,136	$-9,485	0.23	22	$80,621	0.26
0.5	1	0.2	Long	CL-KW	$31,303	$101,800	$-203,600	0.77	13	$305,401	0.23
2	0.2	0.4	Short	CL-KW	$-8,746	$407,201	$-40,720	0.07	14	$447,921	-0.07
0.5	1.4	0.6	Long	CL-NG	$28,488	$41,719	$-116,813	0.92	12	$158,532	0.62
1.5	0.2	0.4	Short	CL-NG	$8,752	$125,156	$-16,688	0.18	39	$141,844	0.16
1	0.2	0.6	Long	CL-PL	$1,296	$9,753	$-1,951	0.28	43	$11,703	0.25
0.5	0.6	0.8	Short	CL-PL	$1,280	$4,876	$-5,852	0.67	18	$10,728	0.25
0.5	0.8	0.2	Long	CL-RR	$10,869	$35,509	$-56,814	0.73	15	$92,322	0.26
1	0.2	0.4	Short	CL-RR	$-1,113	$71,017	$-14,203	0.15	13	$85,220	-0.03
1.5	0.2	0.2	Long	CL-W	$20,443	$172,658	$-23,021	0.22	18	$195,679	0.24
2	0.2	0.4	Short	CL-W	$-4,953	$230,211	$-23,021	0.07	14	$253,232	-0.07
1	0.8	0.2	Long	CT-SI	$157,213	$393,084	$-314,467	0.67	12	$707,551	0.45

0.5	0.4	1	Short	CT-SI	$67,876	$196,542	$-157,233	0.64	11	$353,775	0.38
0.5	1.2	0.4	Long	FC-LB	$8,132	$10,542	$-25,301	0.93	15	$35,843	0.88
0.5	1.4	0.4	Short	FC-LB	$3,845	$10,542	$-29,518	0.83	12	$40,060	0.25
0.5	0.2	0.2	Long	FV-SF	$-338	$6,365	$-2,546	0.25	36	$8,911	-0.08
0.5	1.2	0.2	Short	FV-SF	$4,377	$6,365	$-15,275	0.91	11	$21,640	0.67
2	0.2	0.8	Long	FV-TY	$776	$3,337	$-334	0.31	13	$3,670	0.45
1	1.4	0.4	Short	FV-TY	$981	$1,668	$-2,336	0.83	12	$4,004	0.64
0.5	0.2	0.4	Long	G-HO	$1,751	$26,562	$-10,625	0.33	21	$37,187	0.1
0.5	0.8	0.2	Short	G-HO	$10,605	$26,562	$-42,500	0.77	13	$69,062	0.35
1.5	0.4	0.2	Long	G-KW	$7,364	$59,993	$-15,998	0.31	13	$75,991	0.2
0.5	0.2	0.4	Short	G-KW	$-1,432	$19,998	$-7,999	0.24	17	$27,997	-0.12
1	0.6	0.6	Long	G-NG	$43,604	$78,523	$-47,114	0.72	18	$125,637	0.75
1	1.2	0.2	Short	G-NG	$16,806	$78,523	$-94,228	0.64	14	$172,751	0.2
0.5	0.4	0.2	Long	HG-OJ	$44,361	$177,524	$-142,019	0.58	12	$319,543	0.27
2	0.2	0.2	Short	HG-OJ	$-18,956	$710,095	$-71,010	0.07	15	$781,105	-0.09
2	0.4	0.6	Long	HO-NG	$10,075	$50,477	$-10,095	0.33	12	$60,572	0.34
0.5	0.6	0.4	Short	HO-NG	$2,023	$12,619	$-15,143	0.62	21	$27,762	0.15
0.5	0.2	0.8	Long	KC-SI	$18,320	$37,359	$-14,943	0.64	11	$52,302	0.7
0.5	0.8	0.2	Short	KC-SI	$28,508	$37,359	$-59,774	0.91	11	$97,133	0.97
0.5	1.2	0.2	Long	KW-O	$18,696	$36,392	$-87,342	0.86	14	$123,734	0.42
0.5	0.2	0.6	Short	KW-O	$6,875	$36,392	$-14,557	0.42	19	$50,949	0.27
2	0.6	0.6	Long	KW-RR	$13,001	$53,879	$-16,164	0.42	12	$70,042	0.36
1	0.8	1	Short	KW-RR	$13,695	$26,939	$-21,551	0.73	11	$48,491	0.61
0.5	1.2	0.2	Long	KW-RS	$25,377	$58,608	$-140,659	0.83	12	$199,267	0.33
0.5	0.2	0.4	Short	KW-RS	$4,939	$58,608	$-23,443	0.35	26	$82,051	0.12
2	0.2	0.6	Long	KW-S	$1,119	$38,723	$-3,872	0.12	17	$42,595	0.08
1.5	0.6	0.2	Short	KW-S	$5,304	$29,042	$-11,617	0.42	12	$40,659	0.25
0.5	0.2	0.4	Long	LB-NE	$344	$11,837	$-4,735	0.31	13	$16,572	0.05
1	0.4	0.2	Short	LB-NE	$4,320	$23,675	$-9,470	0.42	12	$33,144	0.25
1	0.4	0.8	Long	LB-NG	$11,188	$47,416	$-18,967	0.45	11	$66,383	0.32
1.5	0.4	0.6	Short	LB-NG	$5,584	$71,125	$-18,967	0.27	11	$90,091	0.13
1	0.2	0.8	Long	O-W	$3,688	$15,688	$-3,138	0.36	11	$18,825	0.39
0.5	1	0.2	Short	O-W	$4,204	$7,844	$-15,688	0.85	13	$23,532	0.48
2	0.2	0.2	Long	PL-W	$38,187	$318,388	$-31,839	0.2	15	$350,227	0.26
2	0.2	0.4	Short	PL-W	$-6,843	$318,388	$-31,839	0.07	14	$350,227	-0.07
1.5	0.4	0.6	Long	RR-S	$4,631	$29,900	$-7,973	0.33	12	$37,874	0.25
2	0.4	0.6	Short	RR-S	$9,403	$39,867	$-7,973	0.36	11	$47,841	0.39
1	0.2	1	Long	RR-SM	$2,632	$14,278	$-2,856	0.32	28	$17,134	0.33
2	0.4	1	Short	RR-SM	$5,090	$28,556	$-5,711	0.32	19	$34,267	0.31
1	1	1	Long	RR-W	$13,869	$21,826	$-21,826	0.82	11	$43,652	0.79
2	0.6	0.6	Short	RR-W	$12,679	$43,652	$-13,096	0.45	11	$56,747	0.43
0.5	0.2	0.6	Long	RS-W	$4,136	$18,070	$-7,228	0.45	20	$25,298	0.32
0.5	0.2	0.2	Short	RS-W	$2,871	$18,070	$-7,228	0.4	25	$25,298	0.23
1.5	0.4	0.4	Long	S-W	$21,118	$95,860	$-25,563	0.38	13	$121,422	0.34
1	0.2	0.8	Short	S-W	$12,761	$63,906	$-12,781	0.33	12	$76,688	0.34
1.5	0.2	0.4	Long	SF-TU	$2,927	$19,650	$-2,620	0.25	12	$22,270	0.29

0.5	0.4	0.4	Short	SF-TU	$-347	$6,550	$-5,240	0.42	12	$11,790	-0.05
0.5	1.4	0.2	Long	SF-TY	$3,825	$5,874	$-16,447	0.91	11	$22,321	0.57
0.5	0.2	0.4	Short	SF-TY	$621	$5,874	$-2,350	0.36	22	$8,224	0.16
1	0.4	0.2	Long	TU-TY	$1,141	$6,334	$-2,534	0.42	12	$8,868	0.25
0.5	0.2	0.4	Short	TU-TY	$653	$3,167	$-1,267	0.44	16	$4,434	0.3
1.5	0.6	0.6	Long	CL-RB	$14,112	$70,659	$-28,264	0.43	14	$98,923	0.28
2	0.6	0.4	Short	CL-RB	$18,823	$94,213	$-28,264	0.38	13	$122,476	0.3
2	0.6	0.8	Long	G-RB	$17,218	$86,192	$-25,858	0.38	13	$112,050	0.3
2	0.8	0.6	Short	G-RB	$15,190	$86,192	$-34,477	0.41	17	$120,669	0.25
0.5	1.4	0.6	Long	HG-RB	$11,995	$32,769	$-91,752	0.83	12	$124,520	0.25
1	1	0.6	Short	HG-RB	$29,770	$65,537	$-65,537	0.73	11	$131,074	0.49
2	1.2	0.8	Long	HO-RB	$5,664	$17,051	$-10,231	0.58	12	$27,282	0.4
1	0.2	1.2	Short	HO-RB	$2,210	$8,526	$-1,705	0.38	13	$10,231	0.43
1.5	0.2	0.6	Long	KW-RB	$6,067	$133,439	$-17,792	0.16	19	$151,231	0.11
1.5	0.6	0.2	Short	KW-RB	$19,255	$133,439	$-53,376	0.39	18	$186,814	0.21
1	0.2	0.4	Long	NG-RB	$-903	$57,379	$-11,476	0.15	26	$68,855	-0.03
1	0.8	0.2	Short	NG-RB	$19,802	$57,379	$-45,903	0.64	11	$103,282	0.38
1.5	0.2	0.6	Long	O-RB	$1,122	$136,983	$-18,264	0.12	16	$155,248	0.02
1.5	0.2	0.2	Short	O-RB	$10,314	$136,983	$-18,264	0.18	38	$155,248	0.17
1.5	0.4	0.8	Long	PA-RB	$8,031	$51,757	$-13,802	0.33	12	$65,559	0.25
2	0.8	0.2	Short	PA-RB	$12,632	$69,010	$-27,604	0.42	12	$96,614	0.25
2	0.8	0.4	Short	PA-RB	$12,632	$69,010	$-27,604	0.42	12	$96,614	0.25
1	0.6	0.6	Long	PL-RB	$17,052	$67,391	$-40,434	0.53	15	$107,825	0.31
1	0.6	0.6	Short	PL-RB	$24,241	$67,391	$-40,434	0.6	15	$107,825	0.44
1.5	0.8	0.2	Long	RB-RR	$43,116	$236,722	$-126,252	0.47	15	$362,974	0.23
1.5	0.2	0.6	Short	RB-RR	$24,898	$236,722	$-31,563	0.21	19	$268,285	0.22
2	0.4	0.4	Long	RB-S	$28,863	$249,444	$-49,889	0.26	19	$299,333	0.21
1.5	0.2	0.8	Short	RB-S	$56,585	$187,083	$-24,944	0.38	13	$212,028	0.53
1.5	0.6	0.4	Long	RB-SM	$15,610	$97,685	$-39,074	0.4	15	$136,759	0.23
1.5	0.4	0.6	Short	RB-SM	$15,175	$97,685	$-26,049	0.33	12	$123,734	0.25
1.5	1	0.2	Long	RB-W	$23,977	$98,987	$-65,992	0.55	11	$164,979	0.28
1.5	0.4	0.6	Short	RB-W	$4,929	$98,987	$-26,397	0.25	12	$125,384	0.09
2	0.2	0.6	Long	ES-TF	$5,954	$86,295	$-8,629	0.15	13	$94,924	0.17
2	0.2	0.2	Short	ES-TF	$843	$86,295	$-8,629	0.1	20	$94,924	0.03
1	0.8	0.4	Long	LB-TF	$2,993	$8,721	$-6,977	0.64	11	$15,698	0.38
0.5	0.8	0.4	Short	LB-TF	$3,632	$4,361	$-6,977	0.94	16	$11,338	1.29
1.5	0.4	0.6	Long	NG-TF	$8,206	$66,838	$-17,824	0.31	13	$84,662	0.2
1	0.6	0.6	Short	NG-TF	$6,150	$44,559	$-26,735	0.46	13	$71,294	0.17
0.5	0.4	0.4	Long	TF-YM	$848	$4,777	$-3,821	0.55	11	$8,598	0.19
0.5	0.4	0.8	Short	TF-YM	$1,174	$4,777	$-3,821	0.58	12	$8,598	0.27

Table 11: Filter0 trading results out-of-sample data

SL	SD	Direction	Spread	Avg $	Max Win	Max Loss	Win%	#	DD	Sharpe

1.4	0.2	Long	AD-FC	$-9,102	$36,420	$-49,005	0.67	9	$85,425	-0.3
1.4	1.2	Short	B-CL	$434	$25,780	$-3,620	0.11	9	$27,320	0.05
0.6	0.6	Short	B-HO	$8,115	$53,996	$-29,748	0.67	6	$83,743	0.24
1.2	0.2	Long	B-KW	$7,427	$85,240	$-59,320	0.67	6	$279,030	0.13
0.2	0.8	Short	B-NG	$-19,521	$0	$-23,870	0	9	$86,440	-9.56
1.2	0.8	Long	B-PL	$5,019	$20,240	$-13,265	0.67	6	$33,310	0.34
0.6	0.2	Long	B-W	$-2,038	$105,010	$-74,040	0.67	9	$129,790	-0.03
0.2	1	Short	B-W	$41,228	$205,360	$-31,965	0.33	6	$200,290	0.38
1.2	0.6	Long	BO-C	$3,427	$36,980	$-20,350	0.67	9	$57,270	0.16
1.2	0.4	Short	BO-KW	$3,521	$55,954	$-27,280	0.6	10	$82,240	0.14
0.2	1.4	Short	BO-RR	$1,864	$10,864	$-1,248	0.29	7	$12,112	0.37
1.2	0.6	Short	BO-W	$8,082	$42,668	$-24,176	0.78	9	$63,214	0.47
0.6	0.2	Long	C-KW	$7,919	$15,998	$0	1	6	$24,713	1.55
1	0.2	Long	C-O	$2	$14,475	$-11,988	0.62	8	$26,500	0
0.6	0.8	Short	C-O	$3,088	$42,038	$-7,062	0.44	9	$48,900	0.19
1	0.2	Long	C-RS	$1,766	$3,395	$0	1	7	$12,477	1.72
0.4	1.2	Short	C-RS	$3,096	$41,389	$-5,060	0.17	6	$26,658	0.17
0.6	0.8	Short	C-W	$1,980	$35,535	$-17,465	0.5	6	$50,363	0.09
0.8	0.2	Long	CD-FC	$-52,945	$15,110	$-87,490	0.17	6	$117,970	-1.51
1.4	0.4	Long	CL-G	$-208	$101,720	$-56,330	0.58	12	$158,050	0
0.6	0.2	Long	CL-KW	$25,073	$177,870	$-138,430	0.8	15	$276,510	0.27
1.4	0.6	Long	CL-PL	$4,988	$21,835	$-14,360	0.71	7	$36,080	0.34
0.8	0.4	Short	CL-PL	$2,171	$25,165	$-9,585	0.5	12	$31,245	0.17
0.2	1.2	Long	CL-RR	$9,350	$76,970	$-16,760	0.38	8	$61,530	0.25
0.6	0.2	Long	CL-W	$7,000	$105,110	$-79,440	0.67	12	$160,040	0.12
0.2	1.2	Short	CL-W	$30,684	$212,710	$-32,690	0.33	9	$171,050	0.33
0.6	0.2	Long	CT-SI	$-340,615	$0	$-794,195	0	10	$1,160,680	-2.08
0.2	0.4	Short	CT-SI	$-92,781	$381,175	$-233,445	0.14	7	$774,860	-0.43
1.2	0.2	Short	FC-LB	$3,337	$173,452	$-30,219	0.22	9	$186,084	0.05
0.2	0.8	Long	FV-SF	$-4,084	$0	$-10,774	0	10	$24,680	-1.62
0.2	1.4	Long	FV-TY	$-680	$0	$-1,618	0	11	$7,376	-1.88
0.6	1.2	Long	G-HO	$19,307	$103,061	$0	1	8	$123,803	0.57
1.4	0.4	Short	G-HO	$5,633	$30,390	$-22,728	0.78	36	$87,918	0.56
0.8	0.2	Long	G-KW	$4,203	$33,365	$-33,635	0.73	11	$52,363	0.26
0.2	1	Short	G-KW	$11,549	$62,215	$-12,472	0.43	7	$56,348	0.39
0.2	0.8	Short	G-NG	$-18,835	$0	$-22,830	0	8	$81,615	-8.58
0.2	0.2	Short	HG-OJ	$96,162	$486,063	$-99,298	0.73	11	$559,693	0.58
0.2	1	Short	HO-NG	$-6,518	$0	$-8,830	0	9	$27,110	-6.09
0.4	0.8	Long	KC-SI	$6,875	$326,345	$-41,584	0.27	15	$365,989	0.07
1.2	0.2	Short	KC-SI	$3,267	$73,176	$-93,666	0.88	8	$106,558	0.07
0.6	0.6	Long	KW-O	$5,920	$90,928	$-59,873	0.69	16	$136,188	0.14
0.4	0.6	Short	KW-O	$7,245	$23,353	$-42,760	0.83	6	$44,110	0.29
1	0.4	Long	KW-RR	$13,649	$18,420	$0	1	12	$43,918	3.71
1.2	0.6	Short	KW-RR	$22,383	$37,835	$0	1	6	$63,838	2.71
0.2	0.2	Long	KW-RS	$-3,266	$104,469	$-29,429	0.31	13	$132,927	-0.08
0.2	1	Long	KW-S	$90	$48,578	$-8,085	0.12	17	$56,010	0.01

0.6	0.2	Short	LB-NE	$3,311	$6,603	$0	1	9	$14,338	1.71
0.4	0.4	Long	O-W	$3,754	$5,602	$0	1	8	$9,262	2.88
0.4	0.8	Short	O-W	$-546	$16,002	$-8,160	0.42	12	$25,448	-0.06
1	0.4	Long	PL-W	$23,516	$103,325	$-17,715	0.9	10	$206,185	0.76
0.6	1	Long	RR-S	$5,611	$52,905	$-16,245	0.5	10	$65,305	0.23
1.2	0.4	Short	RR-S	$3,942	$9,175	$-1,985	0.83	6	$14,610	1.03
0.6	1	Long	RR-SM	$4,238	$74,420	$-14,510	0.21	14	$86,930	0.14
0.2	0.4	Short	RS-W	$-1,719	$42,890	$-9,826	0.25	16	$52,378	-0.11
0.4	1	Short	S-W	$4,602	$196,405	$-37,258	0.25	8	$241,595	0.06
0.2	1	Short	SF-TY	$-3,681	$0	$-9,384	0	10	$28,619	-1.74
0.4	0.6	Long	CL-RB	$554	$89,283	$-43,801	0.33	6	$110,746	0.01
0.4	0.8	Short	O-RB	$-6,221	$107,967	$-51,664	0.36	11	$152,177	-0.11
1.4	0.2	Short	PL-RB	$24,125	$43,267	$0	1	6	$110,375	2.23
0.4	0.2	Long	RB-RR	$-2,821	$165,761	$-84,669	0.44	9	$180,404	-0.03
1	0.2	Long	RB-S	$-7,616	$138,603	$-140,067	0.67	6	$278,670	-0.07
0.6	0.2	Long	RB-W	$4,129	$65,728	$-42,586	0.64	11	$85,217	0.13
0.2	0.6	Long	LB-TF	$-1,099	$14,616	$-2,603	0.07	15	$17,219	-0.25

Table 12: Filter trading results out-of-sample data

PT	SL	SD	Direction	Spread	Avg $	Max Win	Max Loss	Win%	#	DD	Sharpe
1.5	0.2	0.6	Long	AD-FC	$-1,256	$48,668	$-6,489	0.1	21	$55,157	-0.07
2	1.4	1.2	Short	B-CL	$359	$3,047	$-2,133	0.48	66	$5,180	0.15
0.5	0.2	1.4	Long	B-HO	$12,291	$23,084	$-9,234	0.67	6	$32,317	0.74
0.5	0.4	0.2	Long	B-KW	$10,377	$103,974	$-83,179	0.5	10	$187,153	0.11
1	0.2	1.2	Short	B-KW	$65,335	$207,948	$-41,590	0.43	7	$249,537	0.49
0.5	1.2	0.8	Short	B-NG	$6,395	$42,765	$-102,635	0.75	8	$145,399	0.1
0.5	1.2	0.8	Long	B-PL	$1,554	$4,918	$-11,802	0.8	10	$16,720	0.22
1.5	0.8	0.4	Short	B-PL	$2,552	$14,753	$-7,868	0.46	13	$22,621	0.22
0.5	0.2	0.8	Long	B-W	$7,325	$58,762	$-23,505	0.38	8	$82,266	0.17
0.5	0.2	1.4	Short	B-W	$13,869	$58,762	$-23,505	0.45	22	$82,266	0.33
0.5	0.4	1.4	Long	BO-C	$440	$8,050	$-6,440	0.48	42	$14,490	0.06
1	0.4	1.4	Short	BO-KW	$2,506	$20,207	$-8,083	0.38	8	$28,290	0.17
1	1.2	0.6	Long	BO-RR	$1,209	$3,309	$-3,971	0.71	7	$7,280	0.35
0.5	1.4	1	Short	BO-RR	$1,185	$1,655	$-4,633	0.93	14	$6,287	0.72
0.5	1	0.8	Short	BO-W	$1,382	$9,816	$-19,631	0.71	14	$29,447	0.1
0.5	0.2	1.2	Short	C-KW	$-516	$12,094	$-4,838	0.26	39	$16,932	-0.07
1	0.8	0.6	Long	C-O	$1,059	$10,790	$-8,632	0.5	8	$19,422	0.1
0.5	0.6	1.2	Short	C-O	$232	$5,395	$-6,474	0.57	30	$11,869	0.04
0.5	1	1.2	Short	C-RS	$556	$4,900	$-9,800	0.71	17	$14,700	0.08
0.5	1	1.4	Short	C-RS	$286	$4,900	$-9,800	0.69	16	$14,700	0.04
0.5	0.8	0.8	Short	C-W	$-1,014	$11,932	$-19,090	0.58	12	$31,022	-0.06
0.5	0.2	0.8	Long	CD-FC	$-1,448	$34,809	$-13,924	0.26	39	$48,733	-0.07
0.5	1.4	0.2	Long	CL-G	$-2,626	$18,616	$-52,125	0.7	20	$70,742	-0.08

0.5	1.4	0.4	Long	CL-G	$-2,626	$18,616	$-52,125	0.7	20	$70,742	-0.08
0.5	1	1.2	Long	CL-HO	$5,908	$23,712	$-47,424	0.75	12	$71,136	0.18
0.5	0.6	0.6	Long	CL-KW	$12,196	$101,800	$-122,160	0.6	10	$223,961	0.11
0.5	0.6	0.8	Long	CL-KW	$45,790	$101,800	$-122,160	0.75	8	$223,961	0.44
0.5	1	1	Short	CL-NG	$13,886	$41,719	$-83,438	0.78	9	$125,156	0.25
0.5	1.2	0.8	Long	CL-PL	$1,540	$4,876	$-11,703	0.8	15	$16,580	0.23
2	0.8	0.6	Short	CL-PL	$3,881	$19,506	$-7,802	0.43	7	$27,308	0.27
0.5	0.2	1	Short	CL-RR	$15,604	$35,509	$-14,203	0.6	10	$49,712	0.61
0.5	0.4	0.8	Long	CL-W	$13,135	$57,553	$-46,042	0.57	7	$103,595	0.24
1	0.2	1.2	Short	CL-W	$23,001	$115,105	$-23,021	0.33	9	$138,126	0.33
0.5	0.4	1	Long	CT-SI	$-21,986	$196,542	$-157,233	0.38	34	$353,775	-0.13
0.5	0.8	1	Short	CT-SI	$-110,083	$196,542	$-314,467	0.4	10	$511,009	-0.42
0.5	0.4	1.4	Short	FC-LB	$507	$10,542	$-8,434	0.47	72	$18,976	0.06
0.5	0.2	1	Long	FV-SF	$340	$6,365	$-2,546	0.33	46	$8,911	0.09
0.5	1.2	1	Long	FV-TY	$-178	$834	$-2,002	0.65	20	$2,836	-0.11
0.5	0.4	1.2	Long	G-HO	$6,621	$26,562	$-21,250	0.58	12	$47,812	0.27
0.5	0.4	0.4	Long	G-KW	$3,980	$19,998	$-15,998	0.56	9	$35,996	0.21
0.5	0.2	1.4	Short	G-KW	$7,252	$19,998	$-7,999	0.55	11	$27,997	0.5
0.5	0.2	1.4	Short	HO-NG	$821	$12,619	$-5,048	0.33	42	$17,667	0.1
0.5	0.2	1.4	Long	KC-SI	$2,881	$37,359	$-14,943	0.34	85	$52,302	0.12
0.5	1	0.2	Short	KC-SI	$18,659	$37,359	$-74,717	0.83	6	$112,076	0.41
0.5	0.2	1.2	Long	KW-O	$4,194	$36,392	$-14,557	0.37	19	$50,949	0.17
2	0.2	0.8	Short	KW-RR	$11,525	$53,879	$-5,388	0.29	7	$59,266	0.4
0.5	0.2	0.2	Long	KW-RS	$-20	$58,608	$-23,443	0.29	14	$82,051	0
1.5	0.2	1.4	Short	KW-RS	$61,937	$175,824	$-23,443	0.43	7	$199,267	0.58
0.5	0.4	1.4	Long	KW-S	$326	$9,681	$-7,745	0.46	28	$17,425	0.04
0.5	0.4	1	Long	LB-NE	$2,686	$11,837	$-9,470	0.57	7	$21,307	0.24
0.5	0.4	1	Short	O-W	$123	$7,844	$-6,275	0.45	22	$14,119	0.02
0.5	0.4	1.2	Short	O-W	$58	$7,844	$-6,275	0.45	20	$14,119	0.01
1	0.2	1	Long	RR-S	$1,973	$19,934	$-3,987	0.25	32	$23,920	0.19
1	1.4	1	Long	RR-SM	$1,922	$14,278	$-19,989	0.64	25	$34,267	0.12
1.5	0.8	0.4	Short	RR-W	$7,619	$32,739	$-17,461	0.5	6	$50,199	0.28
0.5	0.6	0.2	Short	RS-W	$-3,634	$18,070	$-21,684	0.45	11	$39,754	-0.17
1	0.6	1.2	Short	S-W	$963	$63,906	$-38,344	0.38	13	$102,250	0.02
0.5	0.8	0.8	Short	SF-TU	$256	$6,550	$-10,480	0.63	19	$17,030	0.03
0.5	0.6	0.8	Short	SF-TY	$316	$5,874	$-7,049	0.57	28	$12,923	0.05
0.5	0.6	0.6	Long	TU-TY	$-1,498	$3,167	$-3,801	0.33	6	$6,968	-0.41
0.5	0.4	1.4	Long	CL-RB	$9,401	$23,553	$-18,843	0.67	6	$42,396	0.43
0.5	1.2	0.8	Short	O-RB	$-20,894	$45,661	$-109,587	0.57	7	$155,248	-0.25
0.5	0.4	1.2	Short	PA-RB	$-3,470	$17,252	$-13,802	0.33	24	$31,054	-0.23
1	0.4	0.2	Long	RB-RR	$-7,911	$157,815	$-63,126	0.25	8	$220,941	-0.08
0.5	0.8	0.8	Long	RB-S	$8,295	$62,361	$-99,778	0.67	6	$162,139	0.1
0.5	1	0.2	Long	RB-SM	$-9,323	$32,562	$-65,123	0.57	7	$97,685	-0.18
0.5	0.2	0.8	Long	ES-TF	$4,129	$21,574	$-8,629	0.42	52	$30,203	0.28
0.5	0.2	1.2	Long	LB-TF	$478	$4,361	$-1,744	0.37	49	$6,105	0.17
0.5	0.4	0.6	Short	TF-YM	$1,126	$4,777	$-3,821	0.58	45	$8,598	0.27

Table 13: RSI trading results on out-of-sample data

PT	SL	SD	Direction	Spread	Avg $	Max Win	Max Loss	Win%	#	DD	Sharpe
1.5	0.2	0.4	Long	AD-FC	$-3,766	$49,105	$-8,935	0.07	15	$52,840	-0.26
1.5	0.2	0.6	Long	AD-FC	$-3,766	$49,105	$-8,935	0.07	15	$52,840	-0.26
0.5	0.2	1	Short	B-CL	$-130	$1,700	$-950	0.26	19	$2,650	-0.13
0.5	0.2	0.2	Short	B-NG	$2,243	$46,470	$-22,670	0.33	9	$66,910	0.07
0.5	0.2	0.4	Short	B-PL	$444	$7,740	$-4,840	0.4	10	$10,515	0.09
0.5	1	0.2	Long	BO-C	$-169	$13,180	$-17,180	0.62	8	$29,660	-0.01
1	0.2	0.2	Short	BO-KW	$-2,811	$22,698	$-7,044	0.09	11	$28,388	-0.33
0.5	0.4	0.2	Short	BO-W	$4,517	$12,664	$-9,392	0.67	9	$21,994	0.45
0.5	0.4	0.4	Short	C-KW	$3,211	$14,460	$-10,940	0.57	7	$25,238	0.26
0.5	0.4	0.4	Long	C-O	$-1,374	$5,888	$-5,562	0.33	6	$11,450	-0.25
0.5	0.6	0.2	Short	C-O	$1,694	$6,388	$-6,988	0.67	9	$13,250	0.26
0.5	0.2	0.4	Long	CL-HO	$2,121	$26,124	$-14,210	0.38	16	$39,953	0.12
1.5	0.2	0.2	Short	CL-NG	$-1,314	$128,030	$-22,340	0.12	8	$146,130	-0.02
0.5	1	0.4	Long	CL-PL	$41	$8,580	$-11,020	0.62	8	$19,600	0.01
1	0.4	0.2	Short	CL-PL	$1,510	$11,185	$-6,015	0.42	12	$15,925	0.2
0.5	0.6	0.2	Short	FC-LB	$-6,683	$13,369	$-21,608	0.29	17	$34,977	-0.53
0.5	0.2	0.4	Long	FV-TY	$-296	$1,187	$-1,618	0.21	24	$1,978	-0.4
0.5	0.4	0.2	Short	G-KW	$14,747	$22,303	$-16,510	0.83	6	$32,965	0.96
0.5	0.2	0.2	Short	HO-NG	$969	$14,920	$-8,716	0.36	11	$21,276	0.1
0.5	0.8	0.2	Long	KW-RR	$9,214	$18,015	$-22,145	0.83	6	$40,160	0.6
0.5	1	0.4	Short	KW-RR	$7,775	$16,342	$-28,780	0.83	6	$45,123	0.43
2	0.2	0.8	Long	KW-S	$-5,324	$0	$-7,560	0	12	$28,960	-3.74
1	0.2	0.2	Short	LB-NG	$-1,805	$48,366	$-10,654	0.14	7	$58,428	-0.08
1	0.2	1	Long	RR-S	$-2,747	$20,065	$-6,900	0.09	11	$26,965	-0.36
0.5	0.6	0.6	Long	RR-SM	$762	$11,910	$-12,260	0.57	14	$24,170	0.08
0.5	1.2	0.4	Short	RR-W	$6,108	$14,950	$-26,440	0.83	6	$41,390	0.38
0.5	0.6	0.4	Short	S-W	$5,635	$69,468	$-49,783	0.6	10	$113,213	0.12
0.5	0.2	0.2	Long	TU-TY	$-910	$3,252	$-1,935	0.13	15	$4,922	-0.53
2	0.2	0.2	Short	O-RB	$-24,261	$0	$-30,417	0	7	$143,842	-4.73

Table 14: Moving average trading results out-of-sample data

PT	SL	SD	Direction	Spread	Avg $	Max Win	Max Loss	Win%	#	DD	Sharpe
1.5	0.2	0.6	Long	AD-FC	$-6,509	$0	$-6,489	0	9	$51,629	-Inf
1.5	0.2	0.4	Short	AD-FC	$1,977	$48,668	$-6,489	0.15	13	$55,157	0.1
2	1.2	1	Long	B-CL	$-433	$3,047	$-1,828	0.29	31	$4,875	-0.18
1.5	1.2	1.4	Short	B-CL	$158	$2,285	$-1,828	0.49	41	$4,113	0.09
1.5	0.2	0.2	Short	B-HO	$-9,254	$0	$-9,234	0	7	$52,394	-Inf

1	0.6	0.2	Long	B-KW	$-41,610	$207,948	$-124,769	0.25	8	$332,716	-0.27
1	1	0.8	Long	B-PL	$1,619	$9,835	$-9,835	0.58	12	$19,671	0.16
0.5	0.2	0.4	Short	B-PL	$503	$4,918	$-1,967	0.36	47	$6,885	0.16
1	0.6	0.2	Long	B-W	$-23,525	$117,523	$-70,514	0.25	8	$188,037	-0.27
0.5	1.4	0.6	Long	BO-C	$5,249	$8,050	$-22,540	0.91	11	$30,590	0.57
1	0.2	0.6	Short	BO-C	$6,420	$16,100	$-3,220	0.5	14	$19,320	0.64
2	0.4	0.2	Short	BO-KW	$-2,397	$40,414	$-8,083	0.12	17	$48,496	-0.15
0.5	0.2	0.8	Short	BO-RR	$476	$1,655	$-662	0.5	12	$2,316	0.41
0.5	1.2	0.2	Short	BO-W	$2,094	$9,816	$-23,557	0.77	13	$33,373	0.14
1	0.6	0.2	Short	C-KW	$-2,923	$24,188	$-14,513	0.3	10	$38,701	-0.16
1	1.2	0.2	Long	C-O	$-186	$10,790	$-12,948	0.54	13	$23,738	-0.01
1.5	0.2	0.6	Short	C-O	$2,138	$16,185	$-2,158	0.24	17	$18,343	0.27
1	0.6	0.2	Long	C-RS	$-1,196	$9,800	$-5,880	0.3	10	$15,680	-0.16
0.5	0.8	0.2	Short	C-W	$3,048	$11,932	$-19,090	0.71	7	$31,022	0.2
1	0.4	0.2	Long	CD-FC	$-10,146	$69,618	$-27,847	0.18	11	$80,017	-0.26
0.5	0.2	0.4	Short	CD-FC	$3,777	$34,809	$-13,924	0.36	11	$48,733	0.15
1	1.4	0.2	Long	CL-G	$-7,466	$37,232	$-52,125	0.5	10	$89,358	-0.16
1	1.4	0.4	Long	CL-G	$-12,431	$37,232	$-52,125	0.44	9	$89,358	-0.26
0.5	1	0.4	Short	CL-G	$-3,743	$18,616	$-37,232	0.6	10	$55,849	-0.13
0.5	0.6	0.4	Long	CL-HO	$8,787	$23,712	$-28,454	0.71	7	$52,166	0.35
1.5	0.2	0.2	Short	CL-HO	$-4,466	$71,136	$-9,485	0.06	16	$80,621	-0.22
0.5	1	0.2	Long	CL-KW	$-33,953	$101,800	$-203,600	0.56	9	$305,401	-0.21
1.5	0.2	0.4	Short	CL-NG	$30,574	$125,156	$-16,688	0.33	6	$141,844	0.42
1	0.2	0.6	Long	CL-PL	$816	$9,753	$-1,951	0.24	42	$11,703	0.17
0.5	0.6	0.8	Short	CL-PL	$-20	$4,876	$-5,852	0.55	11	$10,728	0
0.5	0.8	0.2	Long	CL-RR	$-10,673	$35,509	$-56,814	0.5	10	$92,322	-0.22
1.5	0.2	0.2	Long	CL-W	$-23,041	$0	$-23,021	0	9	$177,696	-Inf
1	0.8	0.2	Long	CT-SI	$-157,253	$393,084	$-314,467	0.22	9	$707,551	-0.5
0.5	1.2	0.4	Long	FC-LB	$-7,399	$10,542	$-25,301	0.5	16	$35,843	-0.4
0.5	1.4	0.4	Short	FC-LB	$-7,967	$10,542	$-29,518	0.54	13	$40,060	-0.38
0.5	1.2	0.2	Short	FV-SF	$-1,770	$6,365	$-15,275	0.62	8	$21,640	-0.16
2	0.2	0.8	Long	FV-TY	$171	$3,337	$-334	0.14	14	$3,670	0.14
1	1.4	0.4	Short	FV-TY	$-68	$1,668	$-2,336	0.57	7	$4,004	-0.02
0.5	0.8	0.2	Short	G-HO	$-1,082	$26,562	$-42,500	0.6	10	$69,062	-0.03
1.5	0.4	0.2	Long	G-KW	$-16,018	$0	$-15,998	0	6	$52,898	-Inf
0.5	0.4	0.2	Long	HG-OJ	$-35,525	$177,524	$-142,019	0.33	6	$319,543	-0.22
0.5	0.2	0.8	Long	KC-SI	$-4,905	$37,359	$-14,943	0.19	26	$52,302	-0.23
0.5	0.8	0.2	Short	KC-SI	$-670	$37,359	$-59,774	0.61	23	$97,133	-0.01
0.5	1.2	0.2	Long	KW-O	$-16,657	$36,392	$-87,342	0.57	7	$123,734	-0.25
0.5	0.2	0.6	Short	KW-O	$-6,085	$36,392	$-14,557	0.17	6	$40,319	-0.29
2	0.6	0.6	Long	KW-RR	$-7,428	$53,879	$-16,164	0.12	8	$70,042	-0.3
0.5	1.2	0.2	Long	KW-RS	$-41,046	$58,608	$-140,659	0.5	6	$199,267	-0.38
0.5	0.2	0.4	Short	KW-RS	$13,004	$58,608	$-23,443	0.44	9	$82,051	0.3
2	0.2	0.6	Long	KW-S	$1,432	$38,723	$-3,872	0.12	8	$42,595	0.1
1.5	0.6	0.2	Short	KW-S	$3,148	$29,042	$-11,617	0.36	11	$40,659	0.15
0.5	1	0.2	Short	O-W	$-3,942	$7,844	$-15,688	0.5	6	$23,532	-0.3

2	0.2	0.2	Long	PL-W	$-31,859	$0	$-31,839	0	10	$186,814	-Inf
1.5	0.4	0.6	Long	RR-S	$4,631	$29,900	$-7,973	0.33	6	$37,874	0.24
2	0.4	0.6	Short	RR-S	$-20	$39,867	$-7,973	0.17	6	$47,841	0
1	0.2	1	Long	RR-SM	$1,693	$14,278	$-2,856	0.27	30	$17,134	0.22
2	0.4	1	Short	RR-SM	$1,122	$28,556	$-5,711	0.2	20	$34,267	0.08
0.5	0.2	0.6	Long	RS-W	$1,185	$18,070	$-7,228	0.33	6	$22,700	0.09
0.5	0.2	0.2	Short	RS-W	$131	$18,070	$-7,228	0.29	24	$25,298	0.01
1.5	0.4	0.4	Long	S-W	$18,571	$95,860	$-25,563	0.36	11	$121,422	0.3
0.5	1.4	0.2	Long	SF-TY	$-1,586	$5,874	$-16,447	0.67	9	$22,321	-0.14
0.5	0.2	0.4	Short	SF-TY	$-205	$5,874	$-2,350	0.26	19	$8,224	-0.05
1	0.4	0.2	Long	TU-TY	$-1,287	$6,334	$-2,534	0.14	7	$8,868	-0.38
1.5	0.2	0.2	Short	O-RB	$-18,284	$0	$-18,264	0	11	$153,947	-Inf
1	0.6	0.6	Short	PL-RB	$-9,647	$67,391	$-40,434	0.29	7	$107,825	-0.18
2	0.4	0.4	Long	RB-S	$-49,909	$0	$-49,889	0	7	$280,799	-Inf
2	0.2	0.2	Short	ES-TF	$-8,649	$0	$-8,629	0	25	$67,154	-Inf
1	0.8	0.4	Long	LB-TF	$-1,110	$8,721	$-6,977	0.38	8	$15,698	-0.13
0.5	0.4	0.4	Long	TF-YM	$-674	$4,777	$-3,821	0.37	19	$8,598	-0.15

Table 15: Notable spreads IS Results

Filter0

PT	SL	SD	L/S	Spread	Avg $	Max Win	Max Loss	Win%	#	DD	Sharpe
–	0.2	0.2	Long	Cattle	$1,550	$19,000	$-8,152	0.5	14	$27,153	0.18
–	1.2	0.2	Short	Cattle	$3,555	$12,798	$-698	0.82	11	$39,641	1
–	1.2	1	Long	Crush	$955	$3,831	$-1,148	0.77	13	$4,802	0.7
–	1	0.6	Short	Crush	$480	$2,054	$-1,290	0.79	19	$3,111	0.55
–	0.4	0.2	Long	Crack532	$10,107	$104,271	$-93,837	0.82	11	$128,101	0.22
–	0.2	0.2	Short	Crack532	$14,117	$56,577	$-16,076	0.82	11	$85,518	0.79
–	1.2	0.8	Long	Crack532B	$13,766	$50,660	$-26,358	0.82	11	$75,293	0.57
–	1	0.2	Short	Crack532B	$6,626	$37,990	$-22,679	0.81	27	$59,608	0.44
–	0.4	0.2	Long	Crack321	$6,572	$64,863	$-58,892	0.64	11	$78,510	0.23
–	0.4	0.2	Short	Crack321	$7,441	$31,375	$-9,229	0.82	11	$50,593	0.75
–	1.2	0.6	Long	Crack321B	$6,906	$39,070	$-17,339	0.81	16	$52,254	0.44
–	1	0.6	Short	Crack321B	$6,336	$26,432	$-19,950	0.67	12	$40,934	0.4
–	0.2	0.4	Long	Crack111	$1,655	$27,070	$-17,406	0.67	12	$47,026	0.13
–	0.6	0.2	Short	Crack111	$4,156	$64,003	$-42,626	0.73	11	$121,588	0.16
–	0.2	1	Long	Crack111B	$3,625	$28,912	$-20,803	0.55	11	$45,279	0.21
–	0.4	0.2	Short	Crack111B	$1,460	$43,351	$-30,432	0.69	16	$80,380	0.09

Filter

PT	SL	SD	L/S	Spread	Aisuvg $	Max Win	Max Loss	Win%	#	DD	Sharpe
0.5	0.4	0.2	Long	Cattle	$4,971	$11,188	$-8,950	0.69	13	$20,138	0.52
0.5	0.4	0.6	Short	Cattle	$3,845	$11,188	$-8,950	0.64	11	$20,138	0.38

2	1.2	0.8	Long	Crush	$937	$1,517	$-910	0.77	13	$2,427	0.9
1	1.2	1.2	Short	Crush	$599	$758	$-910	0.92	12	$1,669	1.29
0.5	1.4	1	Long	Crack532B	$6,129	$9,636	$-26,980	0.9	21	$36,616	0.56
0.5	1.4	0.8	Short	Crack532B	$7,462	$9,636	$-26,980	0.94	17	$35,818	0.84
1	1.2	0.8	Long	Crack321B	$6,107	$12,444	$-14,933	0.77	13	$27,378	0.51
0.5	0.8	0.8	Short	Crack321B	$3,891	$6,222	$-9,956	0.86	21	$16,178	0.67
0.5	0.2	0.4	Short	Crack111	$9,414	$39,912	$-15,965	0.45	11	$55,877	0.32
0.5	0.2	0.8	Short	Crack111	$9,414	$39,912	$-15,965	0.45	11	$55,877	0.32
0.5	0.2	0.2	Long	Crack111B	$-1,894	$37,482	$-14,993	0.25	12	$52,474	-0.08

RSI

PT	SL	SD	L/S	Spread	Avg $	Max Win	Max Loss	Win%	#	DD	Sharpe
0.5	0.2	0.2	Long	Cattle	$5,941	$12,642	$-7,085	0.67	12	$18,975	0.71
0.5	0.2	0.4	Long	Cattle	$5,941	$12,642	$-7,085	0.67	12	$18,975	0.71
0.5	0.2	0.2	Short	Cattle	$2,221	$13,748	$-5,560	0.41	17	$19,308	0.25
0.5	0.2	0.4	Short	Cattle	$2,221	$13,748	$-5,560	0.41	17	$19,308	0.25
1	0.4	0.6	Long	Crush	$388	$1,022	$-446	0.64	11	$1,267	0.65
1	0.4	0.8	Long	Crush	$388	$1,022	$-446	0.64	11	$1,267	0.65
0.5	0.8	0.2	Long	Crack532B	$10,918	$20,206	$-16,289	0.92	13	$30,116	1.25
0.5	1.4	0.2	Long	Crack321B	$4,540	$13,567	$-18,607	0.85	13	$24,933	0.44

MA

PT	SL	SD	L/S	Spread	Avg $	Max Win	Max Loss	Win%	#	DD	Sharpe
0.5	0.4	0.2	Long	Cattle	$5,574	$11,188	$-8,950	0.72	18	$20,138	0.6
0.5	0.4	0.2	Short	Cattle	$1,691	$11,188	$-8,950	0.53	17	$20,138	0.17
2	1	1.2	Long	Crush	$876	$1,517	$-758	0.73	11	$2,275	0.84
1	1	1.2	Short	Crush	$601	$758	$-758	0.91	11	$1,517	1.36
1.5	1	1	Long	Crack532B	$11,368	$28,907	$-19,272	0.64	11	$48,179	0.47
1.5	0.2	1.4	Short	Crack532B	$5,486	$28,907	$-3,854	0.29	14	$32,762	0.36
1	1	1	Long	Crack321B	$4,128	$12,444	$-12,444	0.67	12	$24,889	0.34
1.5	0.2	1.4	Short	Crack321B	$3,536	$18,667	$-2,489	0.29	14	$21,156	0.36

Table 16: Notable spreads OOS Results

Filter0

PT	SL	SD	L/S	Spread	Avg $	Max Win	Max Loss	Win%	#	DD	Sharpe
–	1.2	1	Long	Crush	$569	$3,696	$-2,558	0.67	9	$6,254	0.3
–	1	0.6	Short	Crush	$990	$3,824	$-924	0.73	11	$2,919	0.7

Filter

PT	SL	SD	L/S	Spread	Avg $	Max Win	Max Loss	Win%	#	DD	Sharpe

0.5	0.4	0.6	Short	Cattle	$-427	$11,188	$-8,950	0.42	33	$20,138	-0.04
2	1.2	0.8	Long	Crush	$325	$1,517	$-910	0.52	29	$2,427	0.28
0.5	1.4	1	Long	Crack532B	$-2,590	$9,636	$-26,980	0.67	12	$36,616	-0.14
1	1.2	0.8	Long	Crack321B	$-1,264	$12,444	$-14,933	0.5	8	$27,378	-0.09

RSI

PT	SL	SD	L/S	Spread	Avg $	Max Win	Max Loss	Win%	#	DD	Sharpe
0.5	0.2	0.2	Short	Cattle	$-1,905	$13,670	$-9,455	0.21	19	$23,125	-0.24
0.5	0.2	0.4	Short	Cattle	$-1,905	$13,670	$-9,455	0.21	19	$23,125	-0.24
1	0.4	0.6	Long	Crush	$24	$1,105	$-986	0.42	12	$1,951	0.05
1	0.4	0.8	Long	Crush	$24	$1,105	$-986	0.42	12	$1,951	0.05

MA

PT	SL	SD	L/S	Spread	Avg $	Max Win	Max Loss	Win%	#	DD	Sharpe
0.5	0.4	0.2	Long	Cattle	$-2,677	$11,188	$-8,950	0.31	16	$20,138	-0.28
0.5	0.4	0.2	Short	Cattle	$-1,863	$11,188	$-8,950	0.35	17	$20,138	-0.19
2	1	1.2	Long	Crush	$152	$1,517	$-758	0.41	22	$2,275	0.15
1	1	1.2	Short	Crush	$149	$758	$-758	0.61	18	$1,517	0.22