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Pairs Trading in Agricultural Commodity Futures Markets

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ABSTRACT

In this thesis, I study how effective the pairs trading strategy is for generating excess returns using agricultural commodity futures. Historical pricing data was collected for several commodity futures and was first used to select pairs based on the cointegration between their returns. These pairs were later traded over several sample periods between 2013 and 2022, using models of 6-, 12- and 18-month formation period lengths. I found that pairs trading is an effective trading strategy and can outperform the equities market – moreover, the models used performed best when the equity market slumped. Despite the ever-growing pace of technology and speed at which assets can be traded, the market is evidently still capable of creating arbitrage opportunities, namely with agricultural commodity futures.

Keywords:
Arbitrage, Asset Pricing, Futures Pricing, Information and Market Efficiency, Pairs Trading.

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CHAPTER 1 Introduction

Over the past two decades, Wall Street has experienced a growing interest in the use of quantitative methods to reduce speculation and generate excess returns. Among the more simplistic methods of statistical arbitrage, lies the strategy of pairs trading. According to Gatev, Goetzmann, & Rouwenhorst (2006), pairs trading involves two basic steps. First, two stocks with highly correlated past price movements must be found. Typically, these will be found in the same industry; stocks in the same industry tend to be affected by similar external factors, and thus tend to have similar price action. As the spread between the stocks widens, the losing stock is bought while the winning stock is sold short. Based on past price movements, a convergence of the stock prices will generate a profit for the arbitrageur. Academics and investors alike have been surprised to find the effectiveness of such a simple trading strategy. Despite having been empirically tested in the context of stock markets, treasury securities (Nath, 2003), cryptocurrency markets (Fil & Kristoufek, 2020) and commodity futures such as energy and precious metals (Bianchi et al., 2009), there remains an absence in the literature for the effectiveness of pairs trading in agricultural commodity futures. This comes in contrast to Malkiel's (1989) Efficient Market Hypothesis, which theorized that financial markets are efficient with prices reflecting all available information. Should this be observed in the real world, pairs trading within any asset class should not be able to generate abnormal returns.

Previous literature which examines the effectiveness of pairs trading in the US stock market has illustrated compelling evidence that there is a profit to be made. Gatev, Goetzmann, & Rouwenhorst (2006) reported average excess monthly returns of 1.44% for their best model. One possible explanation for this finding is that abnormal returns are partially generated by mean-reversion, which refers to a stock price's tendency to return to its mean after an extreme price movement. It is yet to be determined whether the same principles hold in the commodity futures market; for example, prices may be more dependent on basic supply and demand, as well as market trends. It remains unclear whether there are specific factors which may influence the price action of one asset class but not the other. Other factors, such as transaction costs and short-selling costs remain likely to decrease excess returns regardless of the market. There are several characteristics that differentiate the commodity futures market from other asset classes. This market primarily trades the contracts of physical goods, as opposed to equities in the stock market. Those who trade commodity futures are only required to deposit roughly 10% of the contract value on average, creating a market dominated by leverage, which inevitably leads to greater volatility. Thus, while the abovementioned literature may justify the performance of pairs trading in the US stock market, there remains a lacking discussion of its applicability to agricultural commodity futures and the external factors that may influence excess returns. This paper provides depth to the pairs trading literature using a unique market segment, together with more pertinent data.

In this study, the equity pairs trading strategy studied by Gatev, Goetzmann, & Rouwenhorst (2006) will be partially replicated in the context of commodity futures. This will take form using modern pricing data, aiming to show that this strategy is still capable of generating excess returns years after it was first proposed. Agricultural commodity futures are an interesting market to test the robustness of their findings; in general, commodity futures and stocks behave differently as financial assets. The commodity futures market is composed of hedgers and speculators, whose positions, unlike investors in the stock market, may be affected by multiple external factors related to the securities they trade, such as seasonal conditions and poor harvests. Studying pairs trading in agricultural commodity futures markets may extend our understanding of the effectiveness of this trading strategy in different asset classes and may reveal that abnormal returns are affected by more factors than previously thought. In this thesis, I will explore these ideas in greater detail by answering the following research question: *How effective is pairs trading for generating excess returns in agricultural commodity futures markets?* To the best of my knowledge, this is the first time these topics are linked together.

Implementing a pairs trading strategy will take form in two steps: the formation period and the trading period. Trading pairs will be identified by analyzing the correlation between a chosen sample of agricultural commodity futures over multiple sample periods. During pair formation, the six largest correlations will be used as pairs during the trading period. The sample will be tested using 6-, 12- and 18-month formation periods, which will subsequently be traded in the year that follows. Despite having formation periods of varying lengths, the trading period will remain at 12-months. Historical trading data will be analyzed using a price-ratio between a pair; when it begins to diverge, a position will be opened at a level set at one-point-five historical standard deviations above and below the historical mean. Crossing the lower threshold will signal going long on the underperformer and going short on the overperformer, while the opposite holds true for when the upper threshold is crossed. The standard deviation used to set boundaries in this paper differs from that used by Gatev, Goetzmann, & Rouwenhorst (2006), as I found that there was a lower correlation between agricultural commodity futures than equities, on average. Lowering the boundary increases the chance of a pair being opened in the trading period. The position will be closed once the price ratio for the pair converges back to the historical mean. The historical mean will be calculated on a rolling basis, taking the last 50 trading days into account. The length of the rolling window was determined by testing how long past price movements remain relevant to the current price of a commodity future, for which 50 trading days provided the best results. Should a convergence of prices fail to happen, the position will be closed at the end of the trading period. Using a long-short position of one U.S. dollar per trade, returns will be computed for each trading pair. This process will be repeated for the duration of the trading period, and again throughout the sample from 2013 to 2022. This will provide five separate trading windows, each composed of a total two years, accounting for both formation and trading periods. The data used in this paper will be sourced from the Chicago Board of Trade (CBOT) historical price database.

I hypothesize that the pairs trading strategy in agricultural commodity futures markets will be more successful than the same strategy used in the stock market, with a positive excess return expected. This expectation depends primarily on the higher volatility of commodity futures compared to the stock market, as this asset class tends to have lower liquidity. A higher volatility should present more opportunities throughout the trading period to open positions, wait until convergence, and profit. A commodity futures' price action tends to fluctuate most during times of uncertainty – for example, supply from a major producer may be cut short leading to extreme price fluctuation. The highest returns may be realized during these periods. The effectiveness of the pairs trading strategy will become evident when examining the annualized excess returns, including their significance. I expect that using historical price data for agricultural commodity futures will allow us to explore the effectiveness of statistical arbitrage in this asset class. Nonetheless, I also expect the excess returns of each trading pair to leave sufficient variance unexplained, considering the unique price action of each commodity future over time.

CHAPTER 2 Theoretical Framework

2.1 Effectiveness of Pairs Trading

This study will examine the effectiveness of pairs trading in the agricultural commodity futures market. In simple terms, two assets with a positively correlated price action are chosen as a pair – from here, any large divergence in relative price is traded upon. A short position is opened on the rising asset while a long position is opened on the falling asset. Should history repeat itself, prices will converge, and the trader generates an arbitrage profit. Academic definitions often cite the use of this strategy within hedge funds, who can exploit financial markets that are out of equilibrium (Elliott et al., 2005). Financial professionals have a similar understanding of this trading strategy. Litterman (2004) explained the philosophy of Goldman Sachs Asset Management as follows: despite the assumption that financial markets may not be in equilibrium, they will move towards a rational equilibrium over time. The arbitrage trader aims to maximize their return during periods of deviation.

Pairs trading is an arbitrage trading strategy that has been around since the 1980s. As with most trading strategies, the effectiveness of pairs trading may have decreased following widespread publication and academic research in the years that followed. Do & Faff (2010) argued that increased competition in the hedge fund industry, the primary user of this trading strategy, together with worsening arbitrage risks facing these traders, have contributed most to the falling profitability of pairs trading in equity markets – it remains unclear whether this holds for other asset classes. Furthermore, pairs trading was found to be most effective during periods of prolonged market turbulence, an additional motivation for evaluating the effectiveness of this strategy in the chosen market segment.

In general, commodity futures tend to have lower transaction costs and higher short selling costs when compared to equity markets. Short selling involves borrowing and selling an asset the investor does not own – due to the nature of commodities, a finite supply, storage, and insurance costs contribute to higher costs. Despite this, Bianchi et al. (2009) found that pairs trading can generate statistically significant excess returns in the commodity futures market, even after accounting for higher short-selling costs. It should be noted that this study has a greater focus on energies and precious metals, different from what is proposed in this paper.

2.2 Pairs Trading Performance Relative to Equities

The effectiveness of a trading strategy can only be measured by its returns relative to other strategies or a benchmark, which is most commonly 'the market'. Should the strategy's returns exceed that of a market index, it can be seen as a success. Within the pairs trading framework, there is an additional layer to consider – that is, whether the choice of asset class could impact the success of the strategy. Erb & Harvey (2006) evaluated the tactical value of commodity futures in comparison to equities. They found that on a long-only basis, commodity futures provided few benefits over equities in terms of return, but nonetheless may remain worthwhile due to their diversification benefits. Since arbitrage will entail going both long and short on a commodity future, it will challenge their found results concerning the long-only returns of each model. Additionally, they commented on the success of momentum-based trading strategies in commodity futures, arguing that there is no guarantee of persistence with such a trading strategy.

An important caveat of trading strategies is the source of profitability – does the strategy work better in some markets than others? Chen et al. (2019) found that the profitability of a trading pair is partly explained by delays in information diffusion across the two legs of a pair. Moreover, they suggested that markets with a greater information asymmetry would suffer more from this information delay, and consequently achieve greater excess returns. This built on the work of Andrade et al. (2005), who concluded that pairs trading profits were a compensation for liquidity provision to uninformed buyers. Once again, information asymmetries in the market being traded are linked as a potential source of profitability.

Another variable to consider with specific attention in pairs trading is the formation period. Huck (2013) used an S&P500 sample to evaluate returns of pairs trading and found that they are highly sensitive to the length of the formation period. High positive returns were achieved using 6-, 18- and 24-month formation periods, with an unexpected slump in excess returns under a 12-month formation period. It is yet to be determined whether the same principle applies to commodity futures. A final consideration is the impact of a market's volatility on the effectiveness of pairs trading, as this factor may create more opportunities for opening a pair. In a later study, Huck (2015) examined the impact of volatility timing on the profitability of pairs trading in equities, finding that performance could not be improved further by entering positions during more turbulent time periods. Nonetheless, a higher average volatility over time, such as that found in commodity futures, will create larger price swings and consequently greater arbitrage opportunities for pairs trading to exploit. Jacobs and Weber (2015) took a different approach, using a sample of stocks from both U.S. and international markets. They found that limits to arbitrage are the most important factor in pairs trading profitability, proxied by bid-ask-spreads, liquidity, firm size, and volatility.

2.3 Relationship Between Pairs Trading and Equities

Chen et al. (2022) made use of a trading algorithm to test the effectiveness of pairs trading in commodity futures markets. Their model was trained to select pairs based on correlation coefficients – this was used to calculate the relationship between two assets, while Bollinger Bands were used as indicators for the moving average and standard deviations of the assets. Overall, the authors found a positive relationship between pairs trading and excess returns. The trading model was tested using different inputs over several periods to find the most effective combination, generating a profit of 21.9% over a one-year training period.

This study will partially replicate the pairs trading framework by Gatev, Goetzmann, & Rouwenhorst (2006), developed to test the effectiveness of this strategy in generating significant excess returns. In contrast to this study, the model I use will be tested using commodity futures, more specifically those classified as agricultural products. This market segment is affected differently by external factors, compared to the equity market used to evaluate pairs trading in the original paper. Furthermore, the pair formation in this paper will follow the multicollinearity approach, rather than the minimized sum of squares approach taken the abovementioned authors. These are the two most common methods of identifying pairs in the literature. Having found a positive excess return in equities, I expect there to be a positive, significant excess return for this trading strategy using agricultural commodity futures. After examining the link between pairs trading and generating excess returns, the next step is to formulate a hypothesis that can explain this relationship. Based on previous research and my preliminary analysis, I propose the following hypothesis:

H1: Pairs trading in agricultural commodity futures will produce greater excess returns than the S&P500 over the same trading period.

This hypothesis suggests that pairs trading will not only be effective in the chosen asset class but will also outperform a benchmark market index. Additionally, the relationship between the length of the formation-period and excess returns will be examined through the following hypothesis:

H2: The pairs formed during an 18-month formation period will produce greater excess returns than a 12- and 6-month formation period using pairs trading in agricultural commodity futures.

The second hypothesis will partially follow up on the literature of Huck (2013), testing the sensitivity of excess returns to the length of the formation-period in the agricultural commodity futures sector. It will be tested using a combination of 6-, 12- and 18-month formation period models, with more information used during the formation period expected to increase the effectiveness of the model. The findings of this study will contribute to our understanding of pairs trading, and its effectiveness in different asset classes.

CHAPTER 3 Data

3.1 Pair Selection

To select the correct pairs for trading agricultural commodities, a sample of daily adjusted closing prices was collected for the following futures: Coffee, Cocoa, Corn, Cotton, Feeder Cattle, Lean Hogs, Live Cattle, Oat, Rice, Soybean, Sugar, and Wheat. These commodity futures will be used for pair formation in varying lengths, and then traded throughout the sample period in stages between January 2013 and December 2022. Altogether, the returns sample consists of 1,623 observations for each commodity future, collected from the Chicago Board of Trade historical price database and trading in US Dollars. The chosen sample period has historically been labelled a bull-market and will thus challenge the trading strategy's ability to outperform the S&P500 benchmark.

3.2 Screening of Agricultural Commodity Futures

Adjusted closing prices for the selected commodities were used to calculate daily returns using the formula shown in (1). This process was repeated for each commodity future in the sample, and subsequently a correlation matrix was formed to test for multicollinearity between returns. This is where different formation periods make a difference – for example, a 6-month formation period forms pairs based only on 6-months of return history, whereas an 18-month formation period model would have three times this amount. From here, pairs were constructed (see Appendix 1) in preparation for the trading evaluation.

$$Return = \frac{Adj.Close_n}{Adj.Close_{n-1}} - 1 \tag{1}$$

Table 1

Summary statistics for daily returns, 2013-2022.

Commodity Future	Mean	St. dev.	Min.	Max.
Cocoa	0.0003	0.0004	-0.0851	0.0659
Cotton	0.0002	0.0004	-0.1005	0.0557
Feeder cattle	0.0001	0.0003	-0.0779	0.1104
Lean hogs	0.0008	0.0006	-0.1814	0.2666
Coffee	0.0002	0.0005	-0.0706	0.1251
Wheat	-0.0002	0.0004	-0.0610	0.0807
Live cattle	-0.0002	0.0003	-0.1448	0.0703
Sugar	0.0000	0.0004	-0.0753	0.1102
Corn	-0.0001	0.0004	-0.2355	0.0802
Oats	0.0002	0.0005	-0.1760	0.1668
Rice	0.0004	0.0004	-0.0933	0.1029
Soybeans	0.0001	0.0003	-0.0943	0.0663

Table 1 shows the summary statistics for the sample of returns used to form pairs for the total sample period. Despite having relatively small daily returns on average, the minimum and maximum columns display the commodity future returns' ability to deviate significantly from its opening price on a given day. Pairs will be opened on days with large swings in price movement – when there are large outliers that go beyond one-point-five rolling historical standard deviations, positions can be opened.

During the trading period itself, the pairs trading framework was followed to identify when to open and close positions, which will be discussed in the following section. After the returns for each pair have been generated, they will be summed and weighted equally with the returns of the remaining pairs to form a portfolio for each of the three formation period lengths. Using Equation 2, these will be converted into excess returns and compared to those of the S&P500 during the same period.

$$Excess\ return = Return - rf \tag{2}$$

In the above equation, the 'rf' variable represents the risk-free rate. This will be represented using the average interest rate on 3-month U.S. Treasury Bills at the time of trading. After accounting for the risk-free rate, a comparison can be made between the excess returns of pairs trading agricultural commodity futures and a simple buy-and-hold market strategy. Computing the excess returns for pairs trading over multiple sample periods will allow a comparison and significance analysis in relation to the performance of the S&P500 index over the same periods.

CHAPTER 4 Methodology

To test hypotheses 1 and 2, I will use both hypothesis testing and descriptive statistics to evaluate the effectiveness of pairs trading over the previously mentioned sample periods. These results will be compared to the benchmark S&P500 index throughout the study.

4.1 Pair Formation

Pairs were formed using the historical return data of several agricultural commodity futures. After using adjusted closing prices to calculate the daily returns for each commodity, a correlation matrix was constructed to test the relation between return histories. Starting with 12 individual futures, 66 unique correlations were generated – of these, the six largest positive correlations were chosen as pairs. This process was repeated using formation periods of 6-, 12- and 18-months between 2013 and 2022. A combination of formation and trading period does not exceed two years in length. Despite different lengths of formation period, some pairs proved to be consistent from model to model. Shown in Appendix A, the pairs formed were used to trade in several windows throughout the trading period. These sub-samples will be compared to each other over time and against a benchmark.

4.2 Trading Period

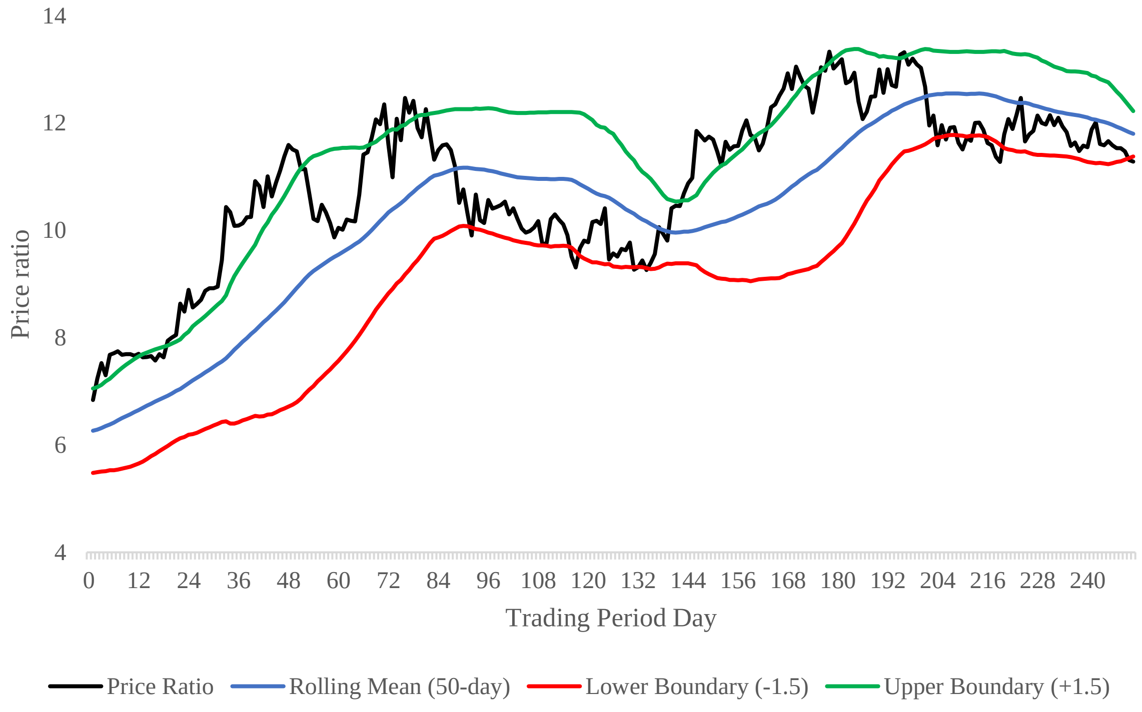
After the pairs have been formed, it is time to begin trading them throughout the sample period, which will be implemented in the following years: 2014, 2016, 2018, 2020 and 2022. There are several components that come together to effectively implement this strategy. This will be further demonstrated using one of the formed pairs from the study: Coffee-Sugar.

Firstly, the price ratio between the two futures is calculated by dividing the adjusted closing price of Coffee by that of Sugar. This process begins 50 trading days before the trading period, allowing for the calculation of a 50-day rolling mean and standard deviation using the price ratio for the first day of trading. This effectively allows the mean and standard deviation to change throughout the trading period to remain in line with relative changes in the price ratio. Using the calculated rolling mean and standard deviation, the upper and lower boundaries can be formed – one-point-five multiplied by the rolling standard deviation, subtracted and added from the rolling mean to form each boundary, respectively. This process is repeated throughout the sub-sample. Once the setup is complete, signals are generated to indicate where positions should be opened and closed. Figure 1 shows the Coffee-Sugar pair and its corresponding 50-day rolling mean, standard deviation, and respective boundaries during the 2014 trading period.

A position can be opened when one of two conditions is met: the price ratio crossing either the upper or lower boundary. It is important to understand the logic of the price ratio; a rising price ratio indicates that the price of Coffee has increased in value relative to Sugar. The Coffee future is overperforming relative to the Sugar future, and thus a signal is generated to open a short position on Coffee and a long position on Sugar if this exceeds the set boundary. The opposite holds true when the lower boundary is crossed. Though the duration that a position is held varies widely, the position will be closed after the price ratio passed through the mean. Additionally, the trading in this study relies on an additional rule: a position will only be opened after at least two trading signals are generated within 10 trading days of each other. The sustained presence of a trading signal fortifies its robustness, confirming it as a genuine mispricing rather than a one-off event.

Figure 1

Price ratio between Coffee and Sugar.



Note. Trading period January 2014-December 2014.

Looking at Figure 1 above, the price ratio goes above the upper boundary at the beginning of the sub-sample. Normally, a position would be opened here and only closed when the price ratio falls below the rolling mean between trading days 84 and 96. Due to the additional rule necessary to open a position, however, the entry of the trade was delayed until additional signals were generated. This led to an entry signal only being printed between trading days 72 and 84 and closing in the days that followed where the price ratio crosses through its mean. This netted a positive return for both long and short positions. In this case, the trading strategy did well to correctly recognize the over and undervalued asset, taking the correct side of the trade as a result. It should be evident that this is not always the case, with both positive and negative cash flows expected from each opened position.

4.3 Excess Return Computation

During the trading period, pairs may open and close several times – or not at all. Positive cash flows are generated for pairs that open and converge through the rolling mean of the price ratio. Gatev, Goetzmann, & Rouwenhorst (2006) propose different methods of computation for excess returns. They make use of the return on committed capital and the return on actual employed capital. The former holds less relevance in this study and is more suitable for models considering a larger number of trading pairs – consequently, it will be omitted. The return on actual capital employed, however, may provide insight into the effectiveness of each model, considering only pairs that were traded in each sample. By scaling returns to the number of pairs that were traded in each period, it represents the funds that were actively employed during the trading period and their respective returns. For example, if only two out of six pairs were traded in a sub-sample, the returns would be weighted to these two pairs rather than the original six. In retrospect, the excess returns calculated under the actual employed capital approach may be more representative due to the flexibility of reallocating and sourcing capital in a trading firm such as a hedge fund.

CHAPTER 5 Results

To evaluate the effectiveness of pairs trading with agricultural commodity futures, returns were computed together with additional metrics over several trading periods. Unless explicitly stated otherwise, it can be assumed that the results in each table are drawn from return data.

Table 2

6-, 12- and 18-month formation period pairs trading models excess returns, sub-samples from January 2014-December 2022.

		6-months	12-months	18-months	S&P500
2014	Excess return	0.0104	0.0212	0.0061	0.1352
	t-statistic	-0.1672	0.0137	-0.2358	
2016	Excess return	0.0752	0.0839*	0.0752	0.1091
	t-statistic	1.3852	1.9232	1.3852	
2018	Excess return	0.0772**	0.0772**	0.0772**	-0.0976
	t-statistic	2.0358	2.0358	2.0358	
2020	Excess return	0.0918	0.1884**	0.1586**	0.1419
	t-statistic	1.0473	2.5509	2.1700	
2022	Excess return	0.1602**	0.1602**	0.1558***	-0.2197
	t-statistic	2.5394	2.5394	3.0102	

Note. * For p<0.10, ** for p<0.05, *** for p<0.01.

Table 2 shows the excess returns of the 6-, 12- and 18-month formation period models between 2014 and 2022. Despite initially underperforming relative to the S&P500 index, all three models exhibited a wide range of returns, encompassing both modest and substantial gains. Holding true to statistical arbitrage, the trading strategy successively produced positive excess returns in each sub-sample. The 6-month model performed below par, only able to generate excess returns higher than the market index in 2018 and 2022 at the 5% significance level. The 12-month model performed best, outperforming the S&P500 index in 2018, 2020 and 2022 at the 5% significance level. Furthermore, it was able to achieve a significant excess return at the 10% level in 2016, edging ahead of the two other models. Lastly, the 18-month model outperformed the market index on three occasions, in 2018, 2020 and 2022. This model produced a statistically significant excess return at the 5% level in 2018 and 2020, improving its significance to the 1% level in 2022. Looking at the data, the pairs trading strategy outperforms the market index most when there are slumps in equity returns, exemplified in 2018 and 2022. Nonetheless, the robustness of the strategy is challenged in 2020, managing to outperform in two out of three models despite a strong 14.19% excess market return. It should be noted that 2020 was an extremely turbulent year for both equity and commodity markets due to the COVID-19 pandemic. Consequently, I do not reject Hypothesis 1, which stated that pairs trading in agricultural commodity futures will produce greater excess returns than the S&P500 over the same trading period.

Building on these findings, Table 3 shows the annual mean excess return and mean return on actual employed capital throughout the sample. The annual mean excess return is highest for the 12-month model, achieving an annual mean excess return of 10.62% throughout the sample, followed by the 18-month model's 9.45% annual mean excess return. The 6-month model relatively underperformed, achieving an annual mean excess return of 8.30%. Despite this, the 6-month model had the lowest standard deviation on an annual basis at 6.05%, relatively lower than the 7.08% and 6.84% standard deviations for the 12- and 18-month models.

Table 3

Annual mean excess return and annual mean return on actual employed capital of pairs trading agricultural commodity futures, January 2014-December 2022.

	6-months	12-months	18-months
Annual mean excess return	0.0830	0.1062	0.0945
(St. Dev.)	(0.0605)	(0.0708)	(0.0684)
Annual mean return on actual employed capital	0.0924	0.1156	0.1039

Note. Excess returns were calculated by computing the average 3-month T-Bill rate for each sub-sample and subtracting this from the end-of-year performance of each model in the sub-samples. The average of each year's excess returns was taken to generate the figures above.

Given these disparate results, I find only partial support for Hypothesis 2, which stated that pairs formed during an 18-month formation period will produce greater excess returns than a 12- and 6-month formation period. While the pairs formed during the 18-month formation period were able to outperform the 6-month formation period model, it was the 12-month formation period model that generated the largest excess returns during the sample period.

Shifting focus to the annual mean return on actual employed capital, this metric accounted for the number of pairs traded and scaled performance to this number. Throughout the sub-sample periods, and thus overall, each model made at least one trade with every pair. Consequently, there was no difference to the return figures in terms of scaling. Should only five pairs have been traded rather than the initially allocated six, the return on actual employed capital would be higher since there is one less trading pair to account for – each pair would have a relatively higher weight in the return computation. The effects of this can be seen in Table 3, where the annual mean return on actual employed capital is only slightly higher than the annual mean excess return since it does not take the risk-free rate into account. There remains no change in the effectiveness of each model, with the 12-month model still outperforming the 18- and 6-month models.

After evaluating the performance of each model over the trading periods, and later the combined average excess returns, there remains several descriptive statistics and other trading data to assess. Table 4 shows several descriptive statistics relevant to the pairs trading strategy. The mean price deviation from boundary indicates how far beyond the upper or lower boundary the price ratio went to trigger an open position signal, on average, and is shown as a percentage relative to the lower or upper boundary itself. Due to the rule established earlier, that which requires at least two open position signals within 10 trading days of each other to open a trade, the mean price deviation from the boundary remained relatively low throughout the sample period. After underperforming relative to the 12- and 18-month models, the 6-month model becomes of interest in this case. In most sub-samples, the 6-month model had a larger deviation from the lower or upper boundary. Paired with its lower performance, this may indicate that a wider spread beyond the boundary is undesirable. As the price ratio moves above or below either boundary, an unfavorable change in asset price could delay the window where a pair is opened, further pushing the price-ratio from the boundary, and delaying the possibility of making a profitable pair trade.

Table 4

Descriptive statistics for pairs trading agricultural commodity futures.

Year	Model	Mean price deviation from boundary (%)	Mean duration pairs are open (trading days)	Mean number of round-trip trades per pair (trading days)
2014	6-months	0.0131	32.9	3.7
		(0.0111)	(10.8)	(1.0)
	12-months	0.0087	29.8	3.8
		(0.0019)	(10.1)	(0.8)
	18-months	0.0082	29.3	4.0
		(0.0013)	(9.7)	(0.6)
	All	0.0102	30.7	3.8
		(0.0065)	(9.7)	(0.8)
2016	6-months	0.0089	28.0	2.0
		(0.0053)	(12.5)	(0.6)
	12-months	0.0085	27.3	2.7
		(0.0049)	(13.2)	(1.8)
	18-months	0.0089	28.0	2.0
		(0.0053)	(12.5)	(0.6)
	All	0.0087	27.7	2.2
		(0.0049)	(11.9)	(1.1)

2018	6-months	0.0082	21.7	3.8
		(0.0055)	(6.1)	(0.8)
	12-months	0.0082	21.7	3.8
		(0.0055)	(6.1)	(0.8)
	18-months	0.0082	21.7	3.8
		(0.0055)	(6.1)	(0.8)
	All	0.0082	21.7	3.8
		(0.0052)	(5.7)	(0.7)
2020	6-months	0.0054	27.3	4.0
		(0.0019)	(19.3)	(1.4)
	12-months	0.0058	19.9	4.5
		(0.0021)	(9.2)	(1.0)
	18-months	0.0051	19.0	4.3
		(0.0020)	(9.7)	(1.0)
	All	0.0054	22.0	4.3
		(0.0019)	(13.3)	(1.1)
2022	6-months	0.0198	25.7	4.0
		(0.0113)	(3.3)	(0.6)
	12-months	0.0198	25.7	4.0
		(0.0113)	(3.3)	(0.6)
	18-months	0.0165	24.5	3.8
		(0.0089)	(4.1)	(0.8)
	All	0.0187	25.3	3.9
		(0.0101)	(3.4)	(0.6)

Note. Standard deviations for each variable reported in parentheses below.

Table 4 also shows the mean duration that pairs are open. In each trading period, the mean number of days pairs remained open was relatively similar, with no large outliers. Looking at the 6-month model, however, there appears to be a consistent trend for an increased length of time that pairs remained open. This may indicate a link between the number of days a pair is opened and its ability to be profitable. When a pair is opened for a longer duration, the probability of an extreme price movement increases. Despite evidence of mean reversion, the mean price ratio can also be crossed in unfavorable conditions. For example, if the long asset falls in price and the short asset rises in price, the condition of passing through the mean price ratio could still be met, despite making a losing trade. The risk involved in each trade tends to increase largely with the number of days the pair is open, though this is limited to some extent using both a rolling mean and rolling standard deviation to set the upper and lower boundaries.

The mean number of round-trip trades is another important factor in pairs trading. During each one-year trading period, there are evidently few opportunities to open a pair – the combined mean for each model ranged from two to four round-trip trades in one trading period. This number is subject to change in line with the number of restrictions set on opening a pair – for example, there may have been more trades if a position was opened on each signal, or if the standard deviation that defines the boundaries was set at a different level.

Having discussed the key descriptive statistics for the actual trading data, Table 5 provides valuable insights into the composition of pairs in each model. Out of the initial 12 agricultural commodities selected before the formation period, only Cocoa and Lean Hog futures failed to be selected into a pair. This may indicate that they are not highly correlated with other agricultural commodity futures, or simply not with those included in the formation period sample. Corn, Soybean, and Wheat futures, on the other hand, were selected most frequently, reflecting their status among the most popular agricultural commodities in terms of production output. By taking up a larger proportion of industry output, the changes in prices for these commodities may cause industry wide shocks that impact the prices of other commodities, leading to an increased correlation between them.

Table 5

Frequency of inclusion in pairs by commodity future.

	Frequency	
Commodity Future	#	%
Corn	38	42.20
Soybean	38	42.20
Wheat	36	40.00
Oat	23	25.60
Feeder Cattle	12	13.30
Live Cattle	12	13.30
Sugar	8	8.90
Coffee	7	7.80
Cotton	4	4.40
Rice	2	2.20

Note. Proportion shown as a percentage relative to the combined number of pairs in the study, 90.

Transitioning from an analysis of the descriptive statistics relevant to pairs trading, the discussion now shifts to the concept of risk assessment, where the focus turns to Value-at-Risk (VaR). VaR is a widely used risk measurement metric and measures the potential losses a trading strategy could incur over a specified period. Table 6 evaluates the daily Value-at-Risk of pairs trading agricultural commodity futures, tested at several different levels. At the 1% level, for example, the 6-

month model VaR suggests a 1% chance of incurring losses greater than 18.49%. The 12-month model expects losses marginally less at 18.18% or more, while the 18-month model suggests significantly less risk, with 13.45% or more in losses expected at the same level. As the confidence level falls, the VaR for the 12- and 18-month model outperform relative to the 6-month model, achieving lower losses until the 10% level. This comes as expected, having seen that the 6-month model performed relatively worse than its lengthier counterparts. At the 25% VaR, the expected losses transform into expected gains for the 12- and 18-month models, displaying their effectiveness in producing an arbitrage profit. Despite being extremely small, the 6-month model still suggests losses at the same confidence level.

Table 6

Daily Value-at-Risk (VaR) of pairs trading.

	6-months	12-months	18-months	All
1%	-0.1849	-0.1818	-0.1345	-0.1873
5%	-0.1036	-0.0713	-0.0745	-0.0824
10%	-0.0558	-0.0458	-0.0432	-0.0487
25%	-0.0015	0.0049	0.0029	0.0028
Min. historical observation	-0.2157	-0.2157	-0.2157	-0.2157

Note. Daily VaR percentiles of 6-, 12- and 18-month long formation period models between January 2014 and December 2022.

After discussing the VaR present in each model, there remains the composition of long and short position returns across models. Table 7 shows the returns generated by the combined long and short positions in each model. There is evidently a large variance in returns, highlighted further by the standard deviation of returns shows in parentheses. This is exemplified in the 12-month model during 2016, where the short positions returned 2.50% with a standard deviation of 18.80%. Here, there were likely several positions that produced a generous return, while being offset by positions that performed poorly. Often, a higher return in either position is offset by either a lower or negative return on the opposite side of the trade. When both sides of a trade can generate a significant positive return, it leads to the best possible performance for the model.

Table 7

Returns to long-short components of each model in pairs trading agricultural commodity futures, sub-samples between 2014 and 2022.

	6-months		12-months		18-months	
	Long	Short	Long	Short	Long	Short
2014	0.0171	-0.0064	0.0055	0.0160	0.0171	-0.0106
	(0.1556)	(0.1621)	(0.1637)	(0.1591)	(0.1557)	(0.1579)
2016	0.0692	0.0092	0.0621	0.0250	0.0692	0.0092
	(0.1189)	(0.1668)	(0.1190)	(0.1879)	(0.1189)	(0.1668)
2018	-0.0165	0.1134	-0.0165	0.1134	-0.0165	0.1134
	(0.0737)	(0.0666)	(0.0737)	(0.0666)	(0.0737)	(0.0666)
2020	0.0629	0.0325	0.1040	0.0880	0.0512	0.1104
	(0.0912)	(0.2165)	(0.1693)	(0.1007)	(0.0788)	(0.0760)
2022	0.2376	-0.0541	0.2376	-0.0541	0.2049	-0.0259
	(0.0998)	(0.1508)	(0.0998)	(0.1508)	(0.1015)	(0.1656)

Note. The returns for both long and short positions were combined and weighted relative to the number of pairs traded in each model.

During the 2020 trading period, for example, the 18-month model performed well, achieving a return of 5.12% and 11.04% on its long and short positions, respectively. Given their relatively low standard deviations in comparison to other models, this was the best possible outcome in terms of risk and return. The table above further shows the arbitrage capability of this strategy, with the combined return of long-short trades remaining positive in each sub-sample.

CHAPTER 6 Discussion

My results show that arbitrage opportunities exist in agricultural commodity futures. Having found evidence of generous excess returns that outperformed the S&P500 over several sample periods, pairs trading in agricultural commodity futures has proven to be successful. This finding is similar to Chen et al. (2022), who likewise found evidence to support the effectiveness of pairs trading commodity futures. Despite having a greater focus on different types of commodities, the strategy's one-year testing period provides reasoning for finding a positive, albeit higher excess return than reported in this study.

Another important factor in pairs trading is the formation period – this determines the historical timeframe necessary to construct the pairs used for trading. In contrast to Huck (2013), who found an unexpected slump in excess returns for the 12-month formation period, pairs trading for agricultural commodity futures performed best under the 12-month formation period. This may come as a consequence of the cyclical nature of commodity futures in relation to equities. Pairs formed over a 12-month period in the commodities sector may be more dependent on each other due to seasonality and supply shocks, for example, and are thus able to create stronger pairs than those formed in the equity market.

In relation to Gatev, Goetzmann, & Rouwenhorst (2006), who tested the effectiveness of pairs trading in equities, my results show that there is a larger premium to be earned in agricultural commodity futures. The pairs trading strategy performed particularly well during times of market turbulence where equities underperformed and may provide a means of diversification when equities are facing market turmoil. Moreover, commodity futures have become increasingly financialized instruments, making it possible for stronger relationships to be established by two separate futures. As markets become more efficient and technology develops, it becomes more difficult to exercise arbitrage – nonetheless, pairs trading provides a methodology to reduce speculation and make profitable trades based on cointegrated assets.

CHAPTER 7 Conclusion

In this thesis I have looked at the effectiveness of the pairs trading strategy, and its ability to generate significant excess returns using agricultural commodity futures. Pairs trading has proven to be an effective trading strategy in several asset classes, most commonly in equities, but also in bonds, foreign-exchange, and cryptocurrency markets. Despite having been studied over the general commodity futures sector, the effectiveness of pairs trading has not been studied independently for agricultural commodity futures. It thus holds importance as an unexplored asset class in the pairs trading literature. Therefore, the question studied in this thesis was: "How effective is pairs trading for generating excess returns in agricultural commodity futures markets?"

To answer this research question, several pairs were formed using agricultural commodity futures. Pairs were constructed on the basis of the strength of their cointegration to other futures, a process that was repeated over three different formation periods: 6-, 12- and 18-months, respectively. The pairs formed over these periods differed from year to year during the sample period, though some years experienced no difference in pairs chosen between models. After setting up the pairs to be traded for each model, the trading period begun. Long and short signals were generated when a criterion of conditions was met. Most importantly, the current price ratio must exceed one-point-five standard deviations above or below the 50-day rolling mean price ratio. To add robustness to the model and ensure trades were made on a genuine arbitrage opportunity, this event must occur at least two times over the span of 10 trading days to open a trade. After establishing the trading rules the models must adhere to, signals were generated, and returns were computed for several sample periods between January 2014 and December 2022. Having computed numerous statistics with the found data, the models generated an average annualized excess return between 8.3% and 10.6% during the sample period. Overall, the 12-month formation period yielded the highest returns, followed by the 18- and then 6-month formation period models. In relation to the equity market, for which a proxy of the S&P500 was used, performance was poor in the years 2018 and 2022. During these market slumps, the pairs trading strategy outperformed the market, delivering significant, positive returns. The difference between the two strategies was most evident during these periods.

This study therefore concludes that although the literature shows there are diminishing excess returns to be earned using this trading strategy, there is evidently an opportunity to generate significant profits using pairs trading in agricultural commodity futures. Combined with the findings from previous studies, it is clear that trading strategies based on arbitrage continue to effectively exploit mispricing in the market and generate attractive returns. With a direct focus on an alternative asset class, the forces of supply and demand, together with other external factors, continue to create price discrepancies between closely related assets.

A potential limitation of this study are the evident gaps in excess returns, as the formation period itself takes up a large portion of trading time. Using longer formation periods creates a shorter period for trading the strategy, and furthermore limits the returns that were computed throughout the sample period. Nonetheless, pairs trading strategies can continually be tweaked to suit the needs of the end user and may further be experimented with to find optimal results. Potentially, future research could exploit a greater amount of data in order to fill the gaps in time and provide a more consistent timeline of returns in reference to a market proxy, be it using pairs trading in equities or agricultural commodity futures.

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APPENDIX A

Formation Period: Pairs formed, 2013-2021.

	2013-14	
6-months (Jan ’13 – Jun ’13)	12-months (Jan ’13 – Dec ’13)	18-months (Jan ’13 – Jun ’14)
Corn-Oat	Corn-Soybean	Corn-Soybean
Corn-Wheat	Corn-Wheat	Corn-Wheat
Oat-Soybean	Oat-Soybean	Oat-Soybean
Feeder-Live	Feeder-Live	Feeder-Live
Cotton-Oat	Rice-Soybean	Corn-Oat
Coffee-Sugar	Coffee-Sugar	Coffee-Sugar
	2015-16	
6-months (Jan ’15 – Jun ’15)	12-months (Jan ’15 – Dec ’15)	18-months (Jan ’15 – Jun ’16)
Corn-Wheat	Corn-Wheat	Corn-Wheat
Corn-Soybean	Corn-Soybean	Feeder-Live
Feeder-Live	Feeder-Live	Corn-Soybean
Corn-Oat	Corn-Oat	Corn-Oat
Oat-Wheat	Soybean-Wheat	Soybean-Wheat
Soybean-Wheat	Corn-Rice	Oat-Wheat
	2017-18	
6-months (Jan ’17 – Jun ’17)	12-months (Jan ’17 – Dec ’17)	18-months (Jan ’17 – Jun ’18)
Corn-Wheat	Corn-Wheat	Corn-Wheat
Corn-Soybean	Corn-Soybean	Corn-Soybean
Feeder-Live	Feeder-Live	Feeder-Live
Soybean-Wheat	Soybean-Wheat	Soybean-Wheat
Coffee-Sugar	Coffee-Sugar	Oat-Wheat
Oat-Wheat	Oat-Wheat	Coffee-Sugar
	2019-20	
6-months (Jan ’19 – Jun ’19)	12-months (Jan ’19 – Dec ’19)	18-months (Jan ’19 – Jun ’20)
Corn-Wheat	Corn-Wheat	Feeder-Live
Corn-Soybean	Corn-Soybean	Corn-Wheat
Soybean-Wheat	Feeder-Live	Corn-Soybean
Cotton-Soybean	Soybean-Wheat	Soybean-Wheat
Feeder-Live	Cotton-Soybean	Cotton-Soybean
Corn-Oat	Coffee-Soybean	Soybean-Sugar

2021-22		
6-months (Jan ’21 – Jun ’21)	12-months (Jan ’21 – Dec ’21)	18-months (Jan ’21 – Jun ’22)
Corn-Wheat	Corn-Soybean	Corn-Soybean
Corn-Soybean	Soybean-Wheat	Corn-Wheat
Soybean-Wheat	Corn-Wheat	Soybean-Wheat
Oat-Soybean	Oat-Wheat	Oat-Soybean
Oat-Wheat	Oat-Soybean	Oat-Wheat
Corn-Oat	Corn-Oat	Sugar-Wheat

Note. Pairs are sorted from top-to-bottom in order of decreasing strength with regard to their correlation coefficient.