



LUND UNIVERSITY FINANCE SOCIETY EST 1991

## TRADING & QUANTITATIVE RESEARCH REPORT

---

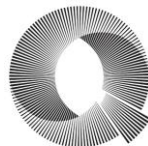
# Skewness strategy on commodities

Comparing the profitability of skewness approaches based on skewness level and closing price when trading commodities

---

In collaboration with:

---



OQAM

---

Analysts:

Doris Rivadeneira Letamendi

Emily Sundqvist

Lazarin Lashkov

## Introduction and Background

In collaboration with OQAM, this project will study two different investment strategies, one based on the level of skewness, and one based on the percentage change of the closing price, to see how the outcome of commodity trading could be maximized. This project will, inspired by the OQAM approach, follow the principles of Occam's razor, or the principle of parsimony, and therefore assume the simplest explanation to be the correct one.

A commodity is a basic good used in commerce that is interchangeable with other goods of the same type. This paper will focus on trade of commodities carried out through futures contracts and will focus on three hard and three soft commodities. As prices of commodities have a trend to move in the opposite direction to stocks, investing in commodities could be a good hedge opportunity during periods of high market volatility. Moreover, commodities can offer very profitable trades, which is why this report will focus on finding the strategy with the highest predictive power of future price movements.



### What is a Skewness Trading Strategy?

A skewness trading strategy is commonly used in the field of systematic investing and quantitative trading. The trading strategy is based on examining the skewness in the returns distribution for a group of assets. This project will focus on commodities, and making an investment decision based on the skewness.

A recent article, “The Skewness of Commodity Futures Returns” by Perez, Frijns, Fuertes, and Miffre [2] encourages traders to take long positions in commodity futures with the most negative skew and short positions in the futures with the most positive skew, in order to generate excess returns that remain after controlling for exposure to well-known risk factors. The testing was done on a skewness window of 365 days, one year.

This is based on the assumption that investors prefer equities with positive skews (or lottery-like pay-offs) and tend to avoid equities with negative skews, which results in overpriced equities with positive skews, hence low expected returns, and underpriced equities with negative skews, with and high expected returns. There are two main factors that support skewness strategy, according to Perez, Frijns, Fuertes and Miffre [2]:

1. Cumulative prospect theory (emphasizes the importance of framing effect, and people's tendency towards loss aversion and overweight of extreme events).
2. Selective hedging practices (investments to reduce the risk to a part of one's portfolio).

This article studies the relationship between past skewness and expected returns in commodities' future markets, an assumption that has based the buy signals for both strategies. In this article, the usage of time-series portfolio analysis and cross-sectional pricing tests has shown that the skewness of commodity futures returns contains information about subsequent returns and the results suggest a negative skewness-expected returns relation. As it is shown, several risk premiums are initially identified, while a tradeable skewness factor that buys the most negatively-skewed commodities and shorts the most positively-skewed commodities has proven to command a premium which is statistically larger than these risk premiums.

## Background

As a result, the long-short skewness portfolio has shown to earn a sizable alpha relative to a battery of benchmarks deemed to capture commodity risk factors. Through cross-sectional pricing tests, the article further establishes that the tradable skewness factor commands a positive premium that is more sizable and more significant than any of the risk factors thus far considered in the literature.

### Price history of the chosen commodities, 2000-2021

The Figures 1-6 (found in the appendix) illustrate the price history from 2000-2021 of the commodities: Corn, Cotton, Soybean, Crude Oil, Silver and Gold. The Figures 1 and 2, show an example to illustrate the price history. Until 2015, the commodities followed mainly the same trends, with highs and lows, which is believed to be due to them being similarly affected by industry-wide events or factors. Due to this pattern, when making the initial testing for the strategy, the scope of the data will be minimized to two different blocks, each 5 years long. The first one from 2000 to 2005 and the second one from 2010 to 2015. When testing the entire dataset, these price histories can be used to explain anomalies, and excess profits or losses.

### Scope

The data used in this project comes from Yahoo Finance and is collected at Kaggle [1]. It includes the historical daily development of prices (open, high, low, close) for futures between 30th of August 2000 and 9th of June 2021. The project focuses on three hard commodities: Gold, Silver and Crude Oil (Brent Oil) and three soft commodities: Corn, Cotton and Soybeans. These are some of the most popular commodities to trade and will provide a broad sense of trade patterns and historical events.

### Hypothesis

The hypothesis for this project is that making trading decisions on commodities by following a skewness strategy leads to more profitable results than following a strategy, based on stop-loss and take-profit levels, or buying in the beginning and holding throughout the entire trading period to finally sell at the end.



Figure 1: Price History from 2000-2021 of Corn



Figure 2: Price History from 2000-2021 of Crude Oil

## Method

### Strategy 1 (Skewness strategy)

The first strategy, the skewness strategy, is based on buying when the skewness of returns has become negative and selling when the skewness level has reached another predetermined skew level, or after a certain number of days if the predetermined skew level has not been reached during this time. In other words, this strategy will depend on two parameters: the holding period before potentially closing a position, and the skew level for producing a sell signal. Since many soft agricultural commodities mostly follow the same price trends because of the same dependence on the environment, the same parameters should be possible to use for multiple soft commodities in order to maximize profitability. Hard commodities, on the other hand, with less relation between each other might show to be more volatile and not follow any patterns as close as soft commodities.

### Strategy 2 (Stop-loss take-profit strategy)

The second strategy, the stop-loss take-profit strategy, is also based on buying when the skew has just gone below the zero value of the skew level but selling at various stop loss and take profit levels. In other words, the sell signal will be based on a percentage decrease and increase, or if the price does not reach the determined percentage level within the given time period, the position will also be closed, just like in the first strategy. To find the most profitable strategy, different variations of the strategy's three changeable parameters: percentage decrease, percentage increase and days to hold a position, will be tested. By having both percentage decrease and increase, this strategy could be used as a risk management strategy.

The two strategies will be compared and analysed with each other. Common traits between the two strategies are that both will have a skew window of 365 days, which means that the skewness is calculated on a 365 day back window for every day, and the parameter, called time period, which indicates the number of days a position is held for. This parameter will be within the same range for both strategies, to be useful for the comparison. The reason behind choosing a skew window of 365 days is because this skew window has been tested and proven by a recent article by Perez, Frijns, Fuertes, and Miffre [2].

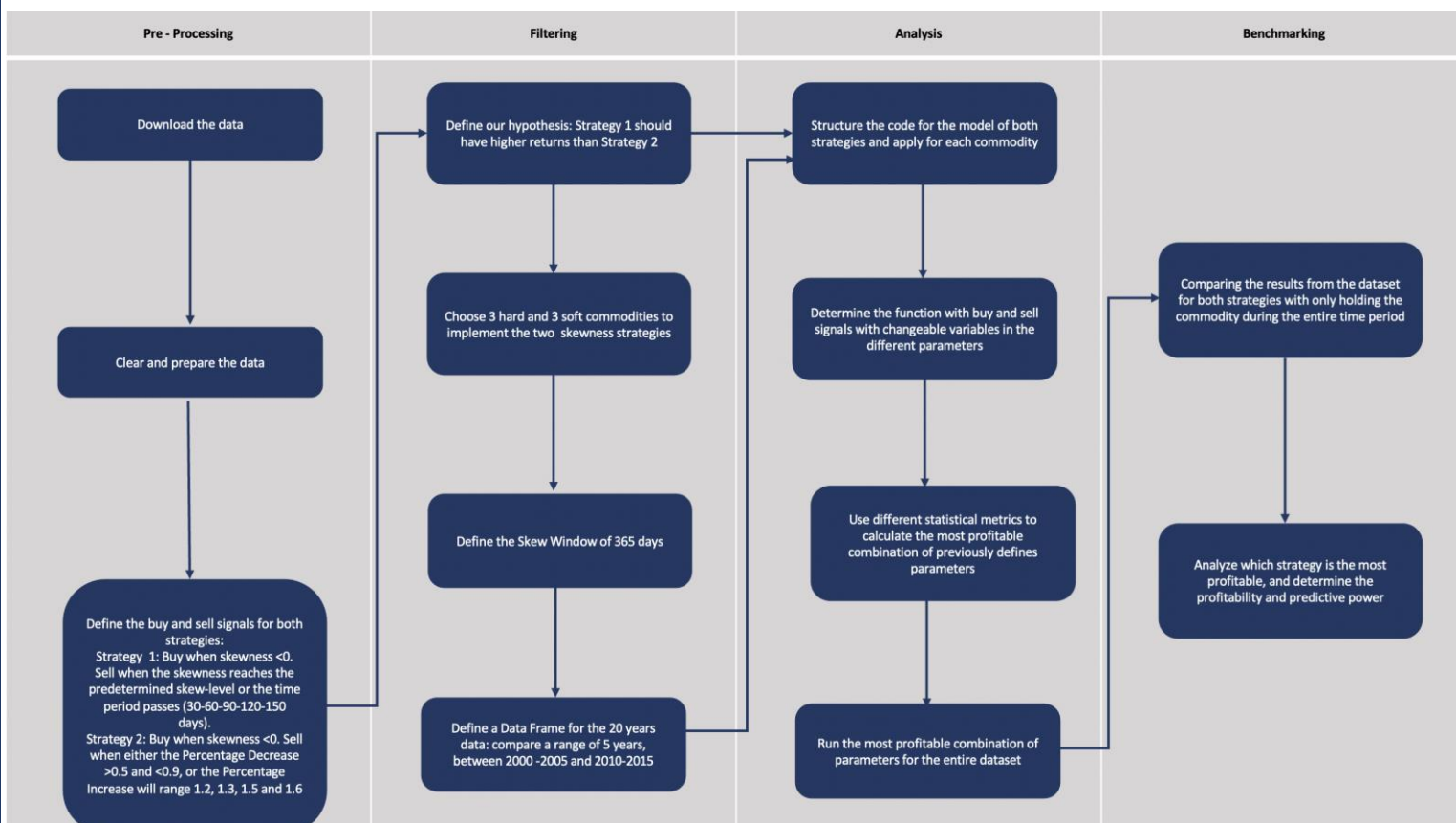


Figure 3: Flow Chart

## Preliminary Testing

### The first tests

The trading strategies in this report will be based on the assumptions proven to be profitable from the studies made from Perez, Frijns, Fuertes, and Miffre and therefore have a negatively-skewed buy signal and a skew-window of 365 days [2]. The two strategies however differ due to their sell signals, the first strategy's sell signal is based on a positive skewness level and as stated in article above, a trading strategy which shorts the most positively-skewed commodity has been proven to have a larger premium. Before deciding on different variables for the sell signal, some preliminary testing was made to see if there existed any pattern of different skew-levels and profits for the different commodities. As seen in Figures 1 and 2 (also Figure 1-6 in the appendix), many commodities follow the same price history which is believed to be due to events that affect cross-industries, and therefore it would be an acceptable hypothesis that the commodities would follow the to a certain level, the same pattern for skew-level as well. To see whether or not this hypothesis is true, some preliminary testing was done for all commodities.

To find the most profitable variables for the sell-signal skew-level for Strategy 1 and see if there were any patterns for the different commodities, the preliminary testing was made with a range of variables for the parameter Skewness Level against a constant time period of 30 days. The variables for skewness were: 0.15, 0.25, 0.35, 0.45, 0.55, 0.65, 0.75, 0.85, 1.00, 1.25, 1.5, 1.75, 2.00. As seen in Figures 4 and 5, where the results are obtained, divided by the three commodities that follow the most similar pattern. The x-axis represents the range of skew-levels for the sell signal while the Y-axis represents the cumulative profits.

As seen in Figure 4, Soybean and Gold each are anomalies, Soybean with a huge negative cumulative profit and Gold with huge positive profits. Studying Figure 5 the other commodities, Silver, Corn, Cotton and Crude Oil can be seen more clearly. What can be said from Figures 4 and 5 is that the commodities do not follow any evident patterns, meaning that finding a trading strategy that works for all, could be an issue. For initial testing for the different datasets, the entire range of variables for skewness should be studied, to see for which commodities the strategy works best for.

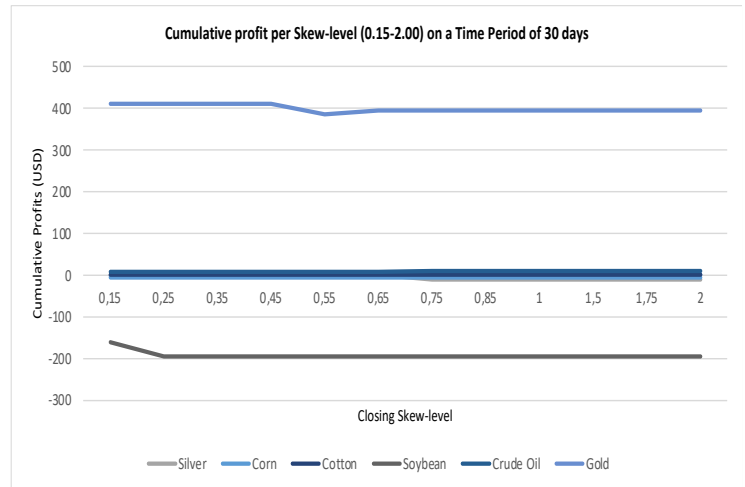


Figure 4: Skew level from 0.15-2 for all the commodities: Silver, Corn, Cotton, Soybean, Crude Oil and Gold

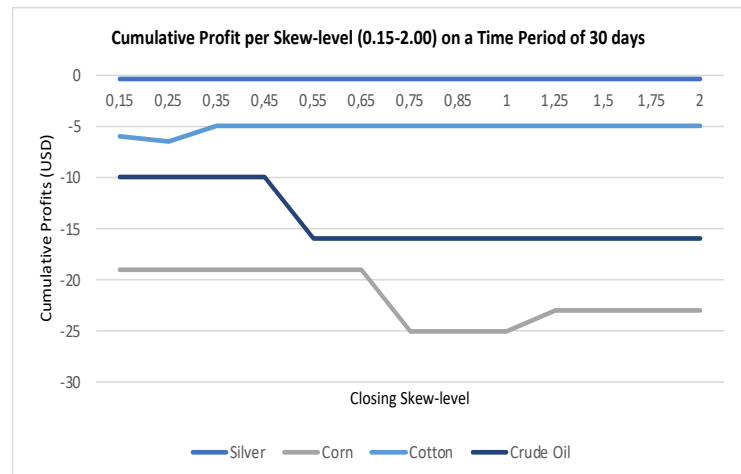


Figure 5: Skew level from 0.15-2 for the commodities: Silver, Corn, Cotton and Crude Oil

For Strategy 2, the parameters defining the sell signal will be based on the closing price change. For the parameters percentage decrease and percentage increase, no preliminary testing was done before defining the range of the variables. The variables were instead chosen to create a form of safety net. By having a range of variables for the percentage decrease of the closing price the strategy is risk management by making sure that each trade only could lose a certain amount. The chosen variables for percentage decrease are: 0.9, 0.8, 0.7, 0.6, 0.5. By also having a sell signal defined by a closing price increase, the strategy would not return extremely high trades, but could also increase the number of trades made. The chosen variables for the percentage increase are: 1.2, 1.3, 1.4, 1.5, 1.6. When finishing the initial testing, the most profitable variables will be chosen to the final strategy which will be tested on the entire dataset (2000-2021).

## Strategy 1 & Strategy 2

---

### Using Python

The dataset for the commodities of interest has been transferred to a Python file and visualized by using the libraries “Pandas” and “Plotly”. Thereafter, the data was cleaned and split into two different periods, both with a 5-year interval, in order to get some initial results without contributing to overfitting in the strategies. The time periods chosen for this project are between 2000 and 2005 as well as 2010-2015. The entire dataset, that will be used for the end results, are between 2000-2021. Thereafter, the skewness has been defined with the library “Scipy” and the skew window is set to 365 days, but it was divided in a data frame of 5 years in periods of 2000-2005 and 2010-2015. The goal with the method is to identify which of the skewness strategies is the most profitable.

After this, the strategy was defined as a function in Python with buy and sell signals with changeable variables in the different parameters. The buy signal is the same for both strategies and is defined as to buy when the skew level is negative, the decision for this is based on the theory presented in the Background and Theory, stating that buying commodities on a negative skew will result in more profitable trades. The condition to only buy if the previous position has been closed was also added.

The different sell signals are then defined depending on the strategy, and another sell condition was also added to make sure that at least one sell signal is traded in each time period. This is defined as, the decided time period subtracted by the number of trades from the last buy signals. The last condition is defined to always make sure that the last trade is a sell in order to always close the strategy.

### Metrics & Parameters

After this, the parameters were defined and these variables were adjusted in order to seek patterns that can be made use of, in order to improve the profitability of the models. Both strategies will have the same numbers of variables in the parameters, for Strategy 1 the Skew level and for Strategy 2 the Percentage Decrease and Percentage Increase as well as the range within the parameter Time Period will be the same for both strategies. Testing will be done within the range of 30, 60, 90, 120 and 150 days to hold the position.

Strategy 1, will run the different metrics: Cumulative Profit, Mean Return, Standard Deviation, Average Position Length, Maximum Return, Minimum Return, Number of Trades, Win Ratio, Profit Factor, Sharpe Ratio, Cumulative Returns, against 5 different values of the skew level: 0.05, 0.15, 0.25, 0.35 and 0.45. Strategy 1 will therefore have 25 possible outcomes.

Strategy 2 will run the parameter Time Period against two other parameters, Percentage decrease and Percentage increase, all against the different metrics: Cumulative Profit, Mean Return, Standard Deviation, Average Position Length, Maximum Return, Minimum Return, Number of Trades, Win Ratio, Profit Factor, Sharpe Ratio, Cumulative Returns. Percentage Decrease will range from 0.9, 0.8, 0.7, 0.6 and 0.5, and the Percentage Increase will range from 1.2, 1.3, 1.5 and 1.6. Strategy 2 will have 125 possible outcomes.

To analyze which strategy is the most profitable, multiple statistical calculations will be used and after that, determine the profitability and to generate testable predictions. The statistics used in this project are the metrics previously stated: Cumulative Profit, Mean Return, Standard Deviation, Average Position Length, Maximum Return, Minimum Return, Number of Trades, Win Ratio, Profit Factor, Sharpe Ratio, Cumulative Returns. The strategies will then be tested for the entire dataset.

## Initial results, Strategy 1

### Plots for trading signals for Strategy 1

In order to visualize the different strategies' trading signals, and how they are related to the different sell signal parameters, two graphs were created for each commodity and strategy which can be seen in Figures 6-11. The green illustrates the buy signal and the red illustrates the sell signal. The upper graph shows the trading signals, based on time and the closing price with the markers green for buying and red for selling. The lower graph shows how the skew level changes over time, which affects the buy signal for both strategies and for Strategy 1, the sell signal. Seen in the Strategy 1's graphs for the 6 commodities with a pre-determined skew-level (of 0.35) and Time Period (of 30 days). The reason for the pre-defined variable for the skew-level is that when creating the initial trading signals, there could only be one variable for the skew-level and when studying Figures 4 and 5, this variable had some of the highest cumulative profits for all commodities. Later, a higher range of variables will be tested in order to find the most profitable for the final strategy. The variable 30 days for the parameter Time Period is chosen based on the findings made by Perez, Frijs, Fuertes, and Miffre [2].

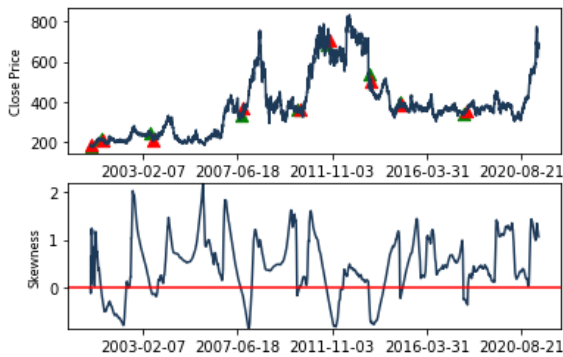


Figure 6: Corn's Price History with buy and sell signals for Strategy 1

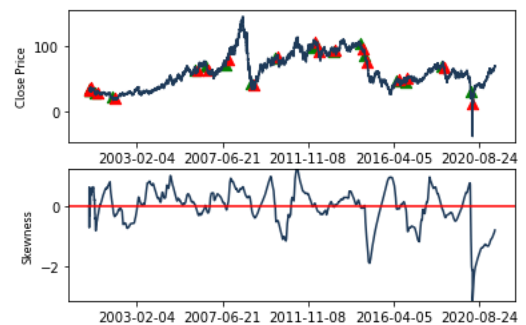


Figure 9: Crude Oil's Price History with buy and sell signals for Strategy 1

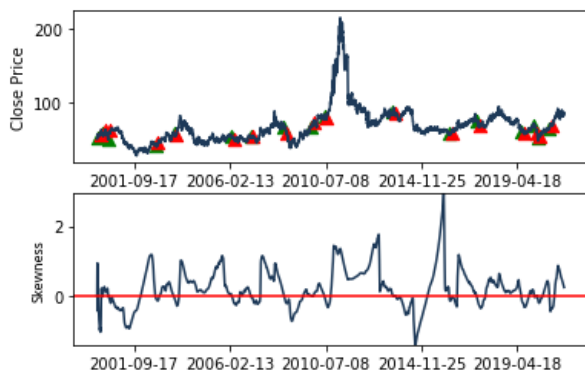


Figure 7: Cotton's Price History with buy and sell signals for Strategy 1

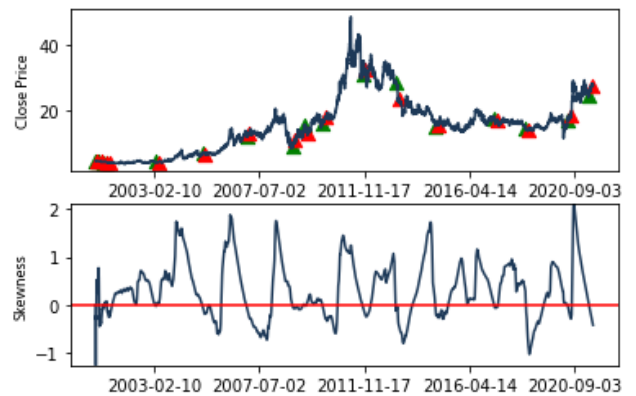


Figure 10: Silver's Price History with buy and sell signals for Strategy 1



Figure 8: Soybean's Price History with buy and sell signals for Strategy 1

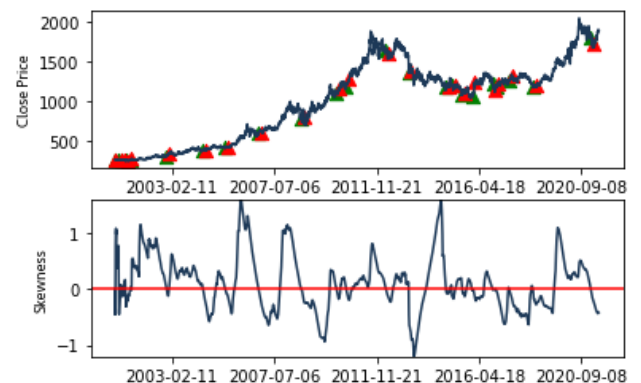


Figure 11: Gold's Price History with buy and sell signals for Strategy 1

## Initial results, Strategy 2

### Plots for trading signals for Strategy 2

Seen in the Strategy 2's graphs for the 6 commodities with a predetermined percentage change of the price (a percentage decrease of 0.9 and a percentage increase of 1.2), as well as the time period (of 30 days), seen in Figures 12-17. Here as well the green illustrates the buy signal and the red illustrates the sell signal. As stated above, the reason for the pre-defined variable for the skew-level is that when creating the initial trading signals, there could only be one variable for each of the percentage changes. 0.9 is the highest percentage decrease and 1.2 is the smallest percentage increase so the results would have the smallest window for percentage change. Later, a higher range of variables will be tested in order to find the most profitable for the final strategy. The variable 30 days for the parameter Time Period is chosen based on the findings made by Perez, Frijns, Fuertes, and Miffre [2]

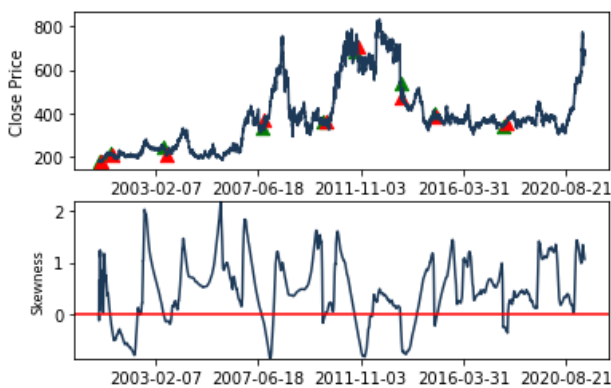


Figure 12: Corn's Price History with buy and sell signals for Strategy 2

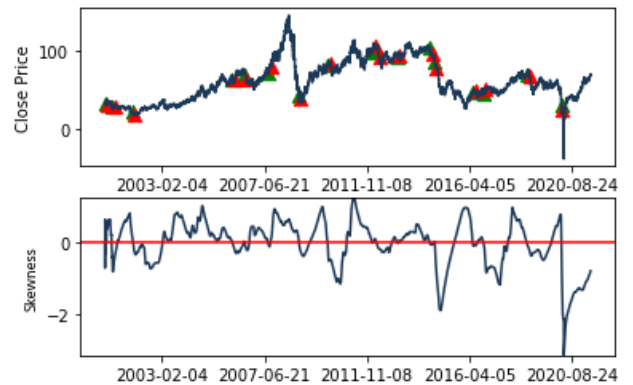


Figure 15: Crude Oil's Price History with buy and sell signals for Strategy 2

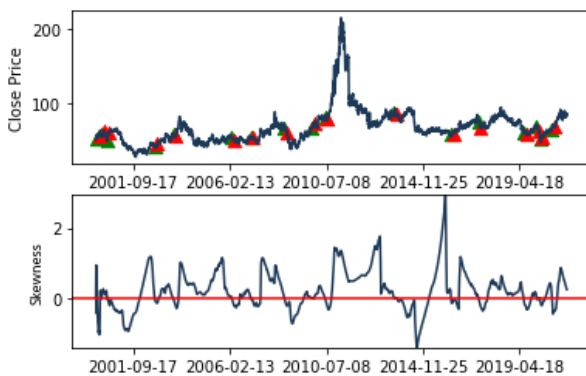


Figure 13: Cotton's Price History with buy and sell signals for Strategy 2

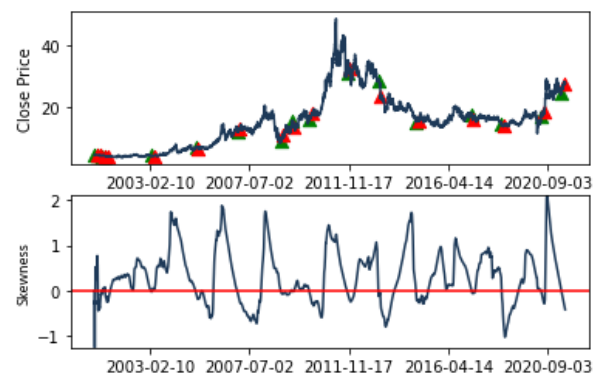


Figure 16: Silver's Price History with buy and sell signals for Strategy 2



Figure 14: Soybean's Price History with buy and sell signals for Strategy 2

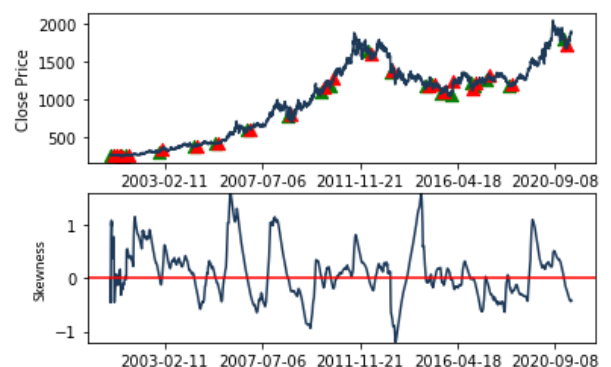


Figure 17: Gold's Price History with buy and sell signals for Strategy 2

## First results, Strategy 1

The first results are based on the data of the six commodities between the years 2000-2005 and 2010-2015. After testing the different variables for the strategy's parameters, there were 80 possible combinations of variables. In order to decide what combination was the most profitable, statistical metrics were further studied to generate testable predictions.

### Important Metrics

Table 1 from the appendix shows the most profitable combinations of the parameters Time Period and Skewness for the commodities Corn and Cotton, Soybean, Silver, Gold and Crude Oil. The data was analyzed by finding the combinations with the largest number of highest metrics that indicate profitability. The metrics chosen to find the combinations with the highest profitability are: Cumulative Profits, Mean Return, Max Return, Win Ratio, Profit Factor, Sharpe Ratio and Cumulative Returns. After studying the combinations, the top 3 most profitable combinations were found for each commodity (from both period 2000-2005 and 2010-2015), giving 18 possible combinations that could be used for the entire dataset (2000-2021), hopefully with a profitable outcome, which can be seen in the Table 1.

### Analysis of Metrics

Examining Table 1, there is a mixture of combinations of variables for each commodity resulting in large differences in the outcome of the metrics. Although the initial testing did not result in a high number of trades, it is high enough to make some conclusions of the data. The strategy results in weakest performance for Crude Oil and Silver and gives the highest return for Cotton, which also has the highest number of trades.

### Further Steps

The most profitable combinations will be found by using time period of 122 days and skewness level of 0.672, which are the mean values taken from the graph below. These parameters will be applied to the full dataset in order to assess the plausibility of the hypothesis.

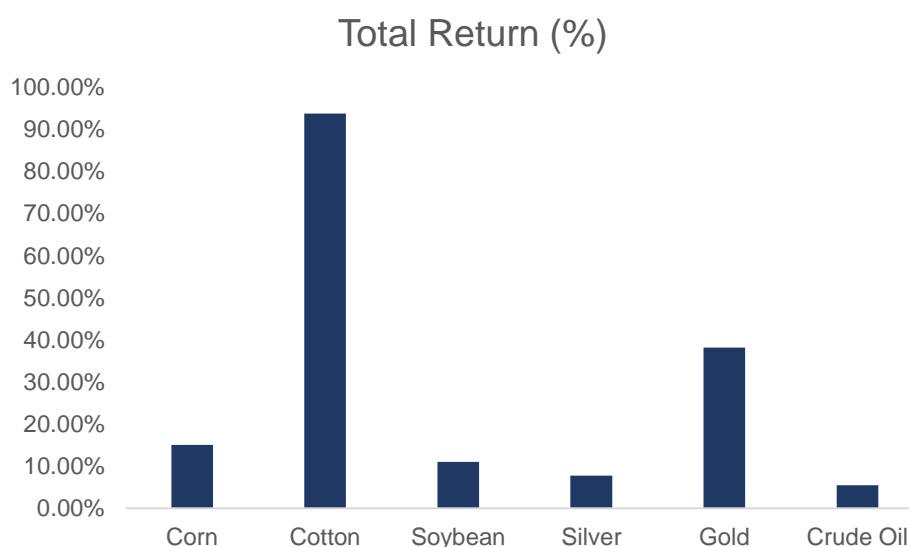


Figure 18: Total returns per most profitable combinations of the parameters between commodities for Strategy 1

## First results, Strategy 2

The first results are based on data of the six commodities between the years 2000-2005 and 2010-2015. After testing the different variables for the strategy’s parameters, there were 125 possible combinations of variables. In order to decide what combination was the most profitable, the statistical metrics were studied to generate testable predictions.

### Important Metrics

Table 2 from the appendix shows the most profitable combinations of the parameters Time period, Percentage decrease and Percentage increase. The data was analyzed by finding the combinations with the largest amount of highest metrics that indicates profitability. The metrics chosen to find the combinations with the highest profitability are: Cumulative Profits, Mean Return, Max Return, Win Ratio, Profit Factor, Sharpe Ratio and Cumulative Returns. After studying the combinations (from both periods 2000-2005 and 2010-2015) the top 3 most profitable combinations were found for commodities Corn and Crude Oil, however for Cotton, Soybean, Silver and Gold, there were multiple combinations with the same metrics results. In order to find the best combination for these commodities, the mean was calculated from the three parameters giving 10 possible combinations that could be used for the entire dataset (2000-2021), hopefully with a profitable outcome, which can be seen in Table 2.

### Analysis of Metrics

Analyzing Table 2, there is a mixture of combinations of variables for each commodity resulting in large differences in the outcome of the metrics. Although there is not a high number of trades, it is high enough to make some conclusions from the data. Seen in Table 19, this strategy as well doesn’t return a positive profit for Silver and gives the highest return for Gold which also has the highest number of trades. For the commodities Corn, Cotton and Crude Oil, the metrics win ratio and profit factor were unable to be calculated due to negative denominators.

### Further Steps

In order to find the best combinations, the mean values for the parameters from the graph below were calculated and will be used when testing the second strategy on the full dataset. The parameter values which will be used are time period of 129 days, percentage decrease of 0.525 and percentage increase of 1.392.

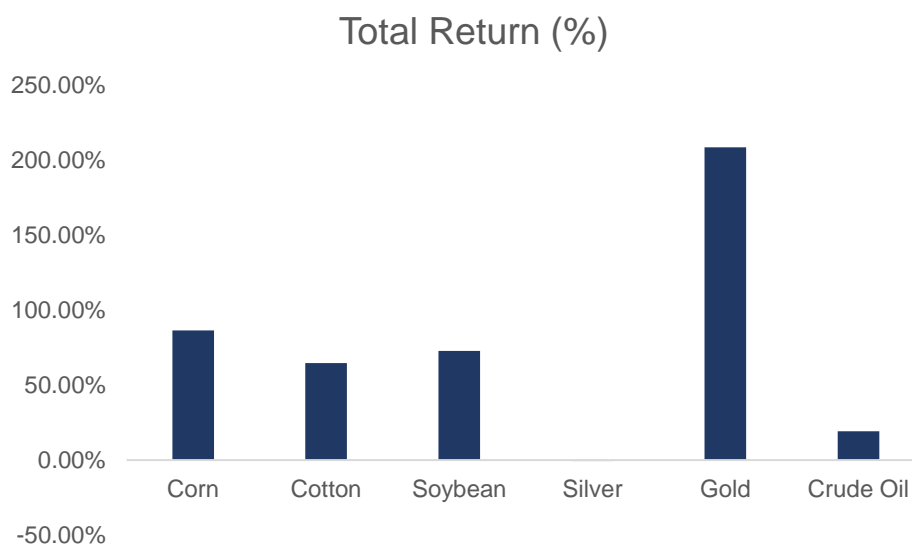


Figure 19: Total returns per most profitable combinations of the parameters between commodities for Strategy 2

## Final results, Strategy 1 and 2, 2000-2021

The final results are based on the best performing combinations of parameters for the six commodities from the initial testing. In other words, the average and median values of these best performing combinations of parameters for the two strategies are applied on the commodities for the entire dataset from 2000 to 2021. In order to assess the performance of the final results, a benchmark will be used: the investment decision to buy in 2000, the beginning of the dataset, hold throughout the entire period and sell at the end.

The following tables depict the final results for both strategies being analysed, while the included measures will be used in the analysis. The main measures of interest are the total returns and Sharpe ratios, indicating the return of the investment relative to its risk. In addition to that, other important measures are win ratio, which is calculated by dividing the amount of trades with positive returns by the ones with negative returns, and profit factor, which shows the proportion of total profit to total loss.

Commodity	Corn			Cotton			Soybean		
	Average	Median	Benchmark	Average	Median	Benchmark	Average	Median	Benchmark
Total Profit (USD)	155.75	274.25	511.5	124.56	91.53	35.55	-1158.50	-557.15	1068.75
Total Return (%)	58.63%	110.62%	285.36%	404.73%	290.82%	69.61%	-63.96%	-32.72%	216.46%
Average Position Length (Days)	159	185	7828	173	185	7828	169	181	7828
Amount of Trades	9	13	1	15	13	1	9	9	1
Win Ratio	0.80	3.33	No losses	2.00	3.33	No losses	0.50	0.50	No losses
Profit Factor	1.52	3.44	No losses	3.91	3.44	No losses	0.043	0.27	No losses
Sharpe Ratio	0.16	0.48	0.76	0.82	0.63	0.31	-0.82	-0.37	0.45

Commodity	Silver			Gold			Crude Oil		
	Average	Median	Benchmark	Average	Median	Benchmark	Average	Median	Benchmark
Total Profit (USD)	16.39	12.63	23.06	917.60	1015.30	1619.30	-16.25	18.70	37.91
Total Return (%)	189.00%	109.90%	467.65%	202.32%	218.62%	591.20%	-1.39%	94.92%	118.28%
Average Position Length (Days)	151	161	7828	163	188	7828	171	163	7828
Amount of Trades	15	14	1	17	16	1	13	15	1
Win Ratio	2.00	1.80	No losses	4.67	4.33	No losses	0.86	4.00	No losses
Profit Factor	2.98	2.04	No losses	20.52	11.39	No losses	0.76	1.15	No losses
Sharpe Ratio	0.46	0.33	1.03	0.68	0.73	1.31	-0.03	0.33	0.56

Table 1: Table of Results from Strategy 1

Commodity	Corn			Cotton			Soybean		
	Average	Median	Benchmark	Average	Median	Benchmark	Average	Median	Benchmark
Total Profit (USD)	230.00	282.15	511.50	96.15	68.21	35.55	-1138.25	-715	1068.75
Total Return (%)	109.96%	122.27%	285.36%	264.95%	182.76%	69.61%	-62.60%	-41.15%	216.46%
Average Position Length (Days)	188	214	7632	181	217	7632	190	220	7632
Amount of Trades	8	8	1	14	12	1	9	8	1
Win Ratio	3.00	1	No losses	1.80	5.00	No losses	0.50	0.33	No losses
Profit Factor	2.32	2.85	No losses	2.96	2.70	No losses	0.059	0.19	No losses
Sharpe Ratio	0.52	0.57	0.76	0.97	0.60	0.31	-1.08	-0.55	0.45

Commodity	Silver			Gold			Crude Oil		
	Average	Median	Benchmark	Average	Median	Benchmark	Average	Median	Benchmark
Total Profit (USD)	15.42	15.37	23.06	896.80	1012.10	1619.30	-34.90	-12.90	37.91
Total Return (%)	156.42%	163.02%	467.65%	190.50%	194.11%	591.20%	-71.44%	-63.52%	118.28%
Average Position Length (Days)	165	189	7632	185	215	7632	167	191	7632
Amount of Trades	14	14	1	16	16	1	13	12	1
Win Ratio	1.33	2.50	No losses	7.00	4.33	No losses	0.63	1.40	No losses
Profit Factor	2.24	2.05	No losses	19.81	9.73	No losses	0.84	1.14	No losses
Sharpe Ratio	0.38	0.33	1.03	0.71	0.58	1.31	-0.04	-0.22	0.56

Table 2: Table of Results from Strategy 2

## Analysis

---

In the final results section, the average of the best performing combinations from each of the six commodities, which has earlier been applied to the entire dataset from 2000-2021, was compared to the benchmark, buying in the beginning of the period and selling in its end. This will show whether it would have been more profitable to utilize the skewness strategy or stop loss-take profit strategy instead of holding the position through the entire period of interest and closing it finally.

### Comparison to most standardized trade

The most important measures for the comparison will be total profits, returns and Sharpe ratios. The results show that all three measures when holding during the entire period are higher than the ones for both strategies for all viewed commodities, except one. Cotton is the only commodity to have beaten the benchmark in terms of total profit, return and Sharpe ratio.

### Comparison between both strategies

When comparing the two strategies with each other, again the average of the best performing combinations for each strategy has been used and important measures of considerations have been total returns, and Sharpe ratio, as well as profit factor. This has led to clear better performance of the first strategy for gold, cotton and crude oil in terms of total returns and Sharpe ratios. In regards to soybeans and silver, the results between strategies have been quite mixed. The stop-loss take-profit strategy has led to higher returns and slightly better Sharpe ratios for corn. Since the first strategy has proven itself to be more profitable for larger amounts of commodities, it can be concluded that it could be more promising to use than the stop-loss take-profit strategy.

### Project Outcome

As the results lead to the conclusion that the two strategies have performed worse than the most standardized model, it is risky to say that their usage in the future can provide promising returns. In addition to this, it is also important to discuss the validity of the strategies and the assumptions behind them.

### Validity Check for Strategy 1

In regards to the skewness strategy, its performance depends to a large extent on the initial assumption for the best skew window as well as the definition of skewness, which has been provided by the Python library "scipy". The skew window, used in the model, has been 365 days and chosen as the best average for all six commodities which have been reviewed. However, better results might be achieved by using different skew windows. Moreover, it is possible that another definition of skewness results in a more profitable skewness strategy. Last but not least, the results from the testing can have been improved by testing more parameter values which might lead to better performing combinations. In this case, the parameters have been the holding period and skew level of triggering a trading signal.

### Validity Check for Strategy 2

In regards to the stop loss-take profit strategy, its performance also depends on the assumptions for the best skew window and the definition of skewness. Another common trait between the two strategies is the holding period parameter. On the contrary, the two other parameters in this strategy are, unlike the first strategy, not directly related to the definition of skewness, but rather the parameter values which were taken into account. Therefore, the potential improvement of this strategy is more limited to increasing the parameter values that have been tested.

To summarize, considering another skew definition and skew window as well as more parameter values to test might result in higher returns or reduced losses and larger Sharpe ratios since these ratios for both strategies have been lower than 1, implying higher risk.

## Conclusion

---

First, an explanation of how the commodity market works is given and the two considered strategies are introduced, as well as the hypothesis. Later follows a more detailed explanation of what skewness is and the first parameter values based on the preliminary testing, as well as relevant tables and graphs. Next, the method is explained and simplified with the help of a flow chart. In addition to this, some graphs are added in order to visualize the method and initial profitability with predetermined values, based on the initial study of patterns of the price movements of futures on the six commodities of interest.

The pages following the method part studies the best performing combinations of the parameters which have been achieved for the two strategies, and their average and medians are taken in order to be used for the final results. These best performing average combinations are benchmarked against the most standardized model in the project, which is to open a position in the first trading day of the dataset and close it in the ending one. As discussed in the analysis, none of the strategies has been able to clearly show better performance than the most standardized model when trading with commodities. In addition to that, the skewness strategy has shown better performance than the stop-loss take-profit strategy. With this said, the findings prove the hypothesis of the project right in terms of the first strategy beating the second one, but wrong in terms of any of these strategies performing better than the most standardized trade.

Future studies within the subject can be made, more detailed testing among the different parameters, both the ones that have been chosen to be constant (skew window and the negative skew-level for the entry point). However, also the changeable variables (skew-level for selling, time period to hold and the percentage changes). By using a larger range of variables within the parameters, as well as testing other constant parameters could yield another result, perhaps a more profitable result. A more developed project could also be made by adding more complex models to the strategy, such as Machine Learning (ML) models or Natural Language Processor (NLP) models.

## References

---

1. Dataset, Commodity Futures Prices:

<https://www.kaggle.com/mattiuzc/commodity-futures-price-history>

2. Fernandez-Perez. A., Frijns. B., Fuertes. A.M., Miffre. J. (2015). The Skewness of Commodity Futures Returns. Journal of Banking and Finance. Available online:

<https://deliverypdf.ssrn.com/delivery.php?ID=505074082114097023100007126003111029049047056084030089124065080009123071127099069002052103055052104116023096120117000065082099028045036041065024016110031008031024071089030027027080121090096092069093091115068120021067009026080104115107106117002120083&EXT=pdf&INDEX=TRUE> [Accessed on the 7 October 2021]

## Appendix A

The following plots illustrates the price history from 2000-2021 of the 6 commodities, Corn, Crude Oil, Cotton, Silver, Soybean and Gold.



Figure 1: Price History from 2000-2021 of Corn



Figure 2: Price History from 2000-2021 of Crude Oil

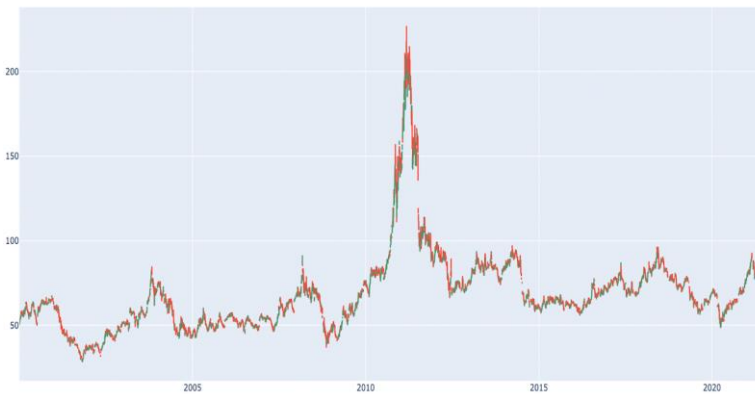


Figure 3: Price History from 2000-2021 of Cotton

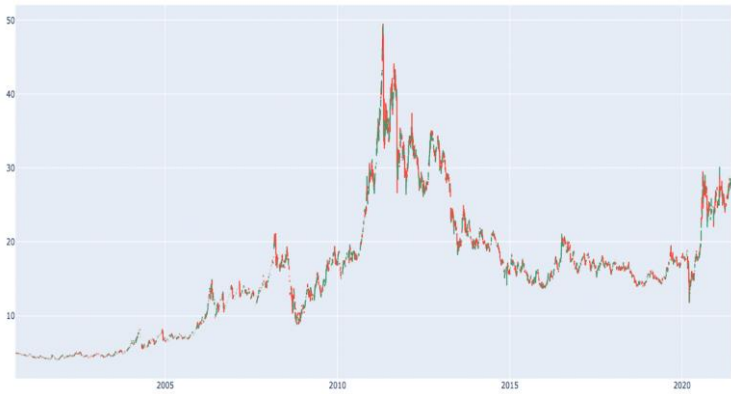


Figure 4: Price History from 2000-2021 of Silver



Figure 5: Price History from 2000-2021 of Soybean

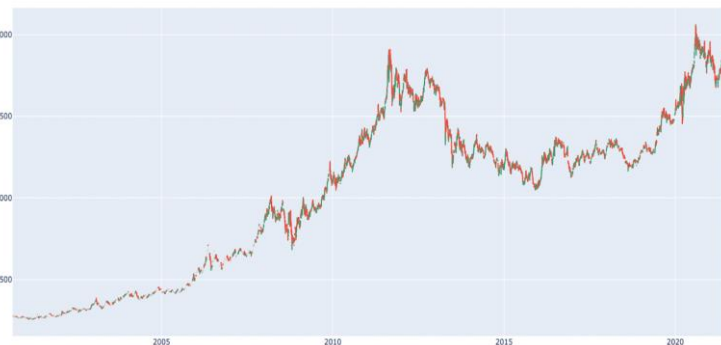


Figure 6: Price History from 2000-2021 of Gold

## Appendix B

The following plots depict the price history of the commodity futures and our trading signals, as well as the level of skewness which leads to the trading signals. The primary is shown on the upper graphs, while the latter on the ones below them.

Corn's Final results. Trading signals (122 days, Skewness: 0.6722)

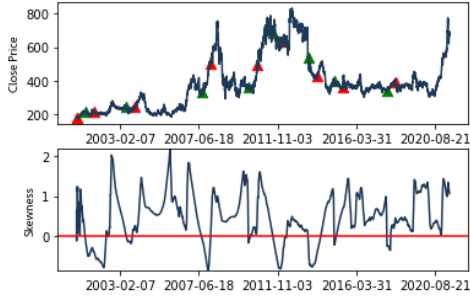


Figure 7: Corn's Final Results from Strategy 1

Soybean's Final results. Trading signals (122 days, Skewness: 0.672)



Figure 8: Soybean's Final Results from Strategy 1

Silver's Final results. Trading signals (122 days, Skewness: 0.6722)

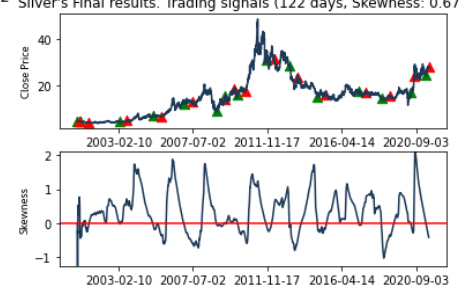


Figure 9: Silver's Final Results from Strategy 1

Cotton's Final results. Trading signals (122 days, Skewness: 0.6722)

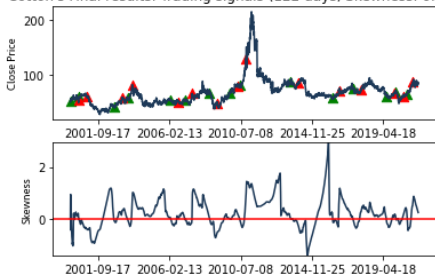


Figure 10: Cotton's Final Results from Strategy 1

Crude Oil's Final results. Trading signals (122 days, Skewness: 0.6722)



Figure 11: Crude Oil's Final Results from Strategy 1

Gold's Final results. Trading signals (122 days, Skewness: 0.6722)

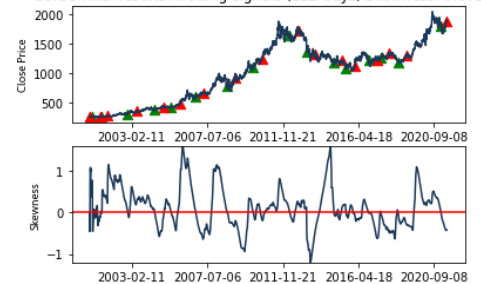


Figure 12: Gold's Final Results from Strategy 1

Corn's Final results. Trading signals (129 days, Pct. decrease: 0.525, Pct. increase: 1.392)

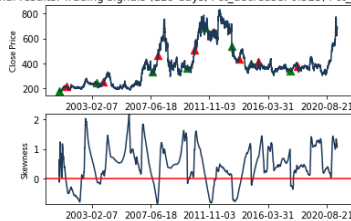


Figure 13: Corn's Final Results from Strategy 2

Soybean's Final results. Trading signals (129 days, Pct. decrease: 0.525, Pct. increase: 1.392)



Figure 14: Soybean's Final Results from Strategy 2

Silver's Final results. Trading signals (129 days, Pct. decrease: 0.525, Pct. increase: 1.392)

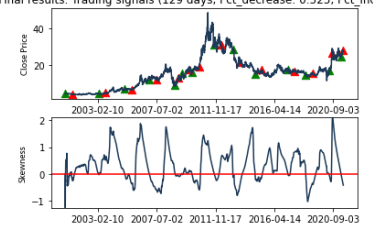


Figure 15: Silver's Final Results from Strategy 2

Cotton's Final results. Trading signals (129 days, Pct. decrease: 0.525, Pct. increase: 1.392)

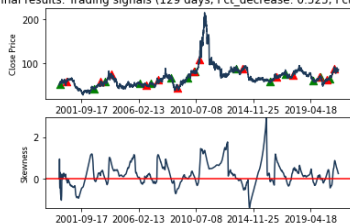


Figure 16: Cotton's Final Results from Strategy 2

Crude Oil's Final results. Trading signals (129 days, Pct. decrease: 0.525, Pct. increase: 1.392)



Figure 17: Crude Oil's Final Results from Strategy 2

Gold's Final results. Trading signals (129 days, Pct. decrease: 0.525, Pct. increase: 1.392)



Figure 18: Gold's Final Results from Strategy 2

## Appendix C

The following two tables depict the first results for the two considered strategies in detail and include all measures discussed on earlier pages.

Commodity	Holding period	Skewness level	Total Profit (USD)	Total Return (%)	Average Position	Amount of Trades	Win Ratio	Profit Factor	Sharpe Ratio
Corn 1	150	1.15	86	16.38%	215	4	0.33	1.66	0.17
Corn 2	150	1.25	76.25	14.42%	215	4	0.33	1.59	0.15
Corn 3	150	1.55	75.75	14.32%	218	4	0.33	1.58	0.15
Cotton 1	150	1.25	69.46	92.26%	184	2	No losses	No losses	1.04
Cotton 2	150	1.45	71.17	94.43%	220	2	No losses	No losses	1.03
Cotton 3	150	1.55	71.17	94.43%	220	2	No losses	No losses	1.03
Soybeans 1	60	1.45	66.25	26.02%	88	3	No losses	No losses	1.48
Soybeans 2	30	0.05	87.25	3.15%	40	3	0.5	151	-0.51
Soybeans 3	30	0.15	99.25	3.96%	43	3	0.5	151	-0.51
Silver 1	150	0.05	0	12.79%	195	4	3	1	0.13
Silver 2	150	0.15	-0.05	9.17%	201	4	3	0.99	0.08
Silver 3	150	0.65	-2.36	1.44%	213	4	1	0.69	-0.01
Gold 1	150	0.15	361.1	33.91%	127	7	6	5.93	0.31
Gold 2	90	0.05	452.5	45.81%	81	8	7	14.92	0.42
Gold 3	90	0.15	368.2	34.74%	99	7	6	194.79	0.36
Crude Oil 1	120	0.45	4.26	2.83%	92	4	3	5.3	0.66
Crude Oil 2	120	0.35	3.79	4.28%	86	4	3	5.51	0.64
Crude Oil 3	150	0.25	12.04	9.33%	205	4	1	4.46	-0.48

Table 1: Profitable combinations of the parameters between commodities for Strategy 1

Commodity	Holding period	% Decrease	% Increase	Total Profit (USD)	Total Return (%)	Average Position	Amount of Trades	Win Ratio	Profit Factor	Sharpe Ratio
Corn 1	150	0.7	1.5	86	86.38%	215	4	No losses	No losses	0.17
Corn 2	150	0.6	1.5	86	86.38%	215	4	No losses	No losses	0.17
Corn 3	150	0.5	1.5	86	86.38%	215	4	No losses	No losses	0.17
Cotton 1	150	1.05	1.5	47.82	64.75%	177	2	No losses	No losses	1.05
Soybeans 1	30	0.56	1.42	75	72.82%	43	3	0.5	151	-0.51
Silver 1	120	0.48	1.48	-0.25	-0.55%	176	3	0.5	0.57	-0.62
Gold 1	90	0.56	1.42	280.6	208.39%	112	7	2.5	14.69	0.15
Crude Oil 1	150	0.7	1.2	14.73	19.24%	190	4	No losses	No losses	-0.38
Crude Oil 2	150	0.6	1.2	14.73	19.24%	193	4	No losses	No losses	-0.41
Crude Oil 3	150	0.5	1.2	14.73	19.24%	199	4	No losses	No losses	-0.44

Table 2: Profitable combinations of the parameters between commodities for Strategy 2

## Disclaimer

### Disclaimer

These analyses, documents and any other information originating from LINC Research & Analysis (Henceforth "LINC R&A") are created for information purposes only, for general dissipation and are not intended to be advisory. The information in the analysis is based on sources, data and persons which LINC R&A believes to be reliable. LINC R&A can never guarantee the accuracy of the information. The forward-looking information found in this analysis are based on assumptions about the future, and are therefore uncertain by nature and using information found in the analysis should therefore be done with care. Furthermore, LINC R&A can never guarantee that the projections and forward-looking statements will be fulfilled to any extent. This means that any investment decisions based on information from LINC R&A, any employee or person related to LINC R&A are to be regarded to be made independently by the investor. These analyses, documents and any other information derived from LINC R&A is intended to be one of several tools involved in investment decisions regarding all forms of investments regardless of the type of investment involved. Investors are urged to supplement with additional relevant data and information, as well as consulting a financial adviser prior to any investment decision. LINC R&A disclaims all liability for any loss or damage of any kind that may be based on the use of analyzes, documents and any other information derived from LINC R&A.

### Conflicts of interest and impartiality

To ensure LINC R&A's independence, LINC R&A has established compliance rules for analysts. In addition, all analysts have signed an agreement in which they are required to report any and all conflicts of interest. These terms have been designed to ensure that COMMISSION DELEGATED REGULATION (EU) 2016/958 of 9 March 2016, supplementing Regulation (EU) No 596/2014 of the European Parliament and of the Council with regard to regulatory technical standards for the technical arrangements for objective presentation of investment recommendations or other information recommending or suggesting an investment strategy and for disclosure of particular interests or indications of conflicts of interest.

### Other

This analysis is copyright protected by law © BÖRSGRUPPEN VID LUNDS UNIVERSITET (1991-2021). Sharing, dissemination or equivalent action to a third party is permitted provided that the analysis is shared unchanged.