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TRADING & QUANTITATIVE RESEARCH REPORT

Evaluating Commodity Trading Strategies

Comparing Traditional Trend Strategies to Machine Learning in Commodity Trading

In collaboration with:

OQAM

Analysts:
Victor Ritseson
Balasurya Sivakumar
Binh Minh Tran

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Introduction & Theory

Introduction

This report aims to compare a commonly used momentum trading strategy with a machine learning (ML) approach in the commodity futures markets. The momentum strategy involves investing in well performing securities and selling them first when the prices have reached the peak (Barone, 2021). The idea is simple: past winners continue to do well in the medium-term and past losers continue to fall in the medium-term. This way of investing has been quite popular among traders since its popularisation in the 1990s (Barone, 2021).

Given this, in collaboration with OQAM Asset Management, Malmö, this paper attempts to test this trading strategy on the commodity futures markets and further compare it with a machine learning approach. To implement the momentum strategy, the moving average convergence divergence indicator (MACD) has been considered. The MACD indicator uses the relative strength of two different moving averages while indicating the momentum in the market, i.e. the indicator relies on a “signal line” and “MACD” line which depicts the momentum in the market (Adithyan, 2021). A detailed explanation of this is given in the theory section. Since, the analysis is conducted on the commodity futures market for a time span of 15 years from 2005 to 2020, this report use three MACD measures: short MACD (12-26), medium MACD (40-80), and long MACD (120-160). The three measures will help in understanding the trends across different time lengths.

For ML, the Random Forest algorithm is used. The details of this ML approach are explained in the theory section. Finally, it is also important to note that in this report we are analysing 11 commodity futures, including metals (gold, silver, copper, palladium, platinum); agricultural commodities (wheat, soybean, corn), and energy commodities (crude oil, natural gas).

Theory

Commodity futures are a compliance to purchase or sell commodities at a particular time in the future at a specific price at a specific quantity. There are some benefits of futures contracts when engaging in the commodities market. This can be seen as an alternative to the conventional stock market or ETFs. Further, there is a chance for substantial earnings, and if a financial investor can open a minimum-deposit account, he can handle full-size deals (that, in any case, might be hard to manage). Subsequently, it is reachable to take long or short positions on future deals.

Future markets fulfill two essential functions. The first is value revelation: future markets provide a focal marketplace where all purchasers and dealers can interact to decide prices. The second function is to transfer price hazards: futures allow individuals a chance to establish prices for future delivery. This price hazard measure is called hedging. For investors, commodities can be a significant style of differentiating their portfolios beyond conventional securities.

In the field of commodities, simply explained, momentum strategies involve purchasing the commodity futures that performed well in the past and selling those that underperformed in the market, thus creating a relative-strength portfolio that yields the return in the long run. It was demonstrated that financial investors could utilise different blends of positioning periods and holding periods and these methodologies would in any case be rewarding (Miffre et al, 2007). Delightfully, the momentum returns are likewise found to have low relationships with the profits of traditional asset classes, making the commodity-based relative-strength systems a great contender for incorporation in an enhanced portfolio.

Moving Average Convergence Divergence

One of the most well-known indicators that are being used is the MACD, the indicator uses a combination of a 26 day and a 12 day period exponential moving average (EMA). By using the difference between the two indicators a signal line is created which when intercepted triggers a buy or sell signal. The EMA in contrast to simple moving averages, weighs in recent prices which is done by equation 2. The smoothing factor is commonly set to the value 2 which is the case for this report. Equation 1 shows how the indicators are calculated.

Theory (continued)

$$EMA_t = [V_t*(\frac{s}{1+d}) + EMA_y*(1 - \frac{s}{1+d})$$

$$MACD = EMA_{12} - EMA_{26}$$

EMA_t = EMA today; V_t= Value today; EMA_y = EMA yesterday

s = Smoothing; d = Number of days

Equation 1. Mathematical formula for calculating MACD and EMA.

In Figure 1 we can see a fully implemented MACD indicator. In the top panel, the candlestick bars depict the opening and closing prices. The middle panel depicts the signal and MACD line. As stated above, buy/sell signals are triggered when the MACD and signal lines intersect. Finally, the bottom most panel is histogram of Futures Volume traded.

Random Forest

Random forest is a machine learning algorithm that is utilised broadly in regression and classification issues. It produces decision trees on distinctive models and selects the most votes for classification and median with regard to regression. Amongst the most critical factors of the random forest is that it can deal with the data set including constant factors on account of regression and categorical factors on account of classification. It utilises elements of randomness when assembling every individual tree to attempt to make an uncorrelated forest of trees in which prediction is more proper than that of all individual trees. Random forests are terrific with immense data since we are working with groups of data.

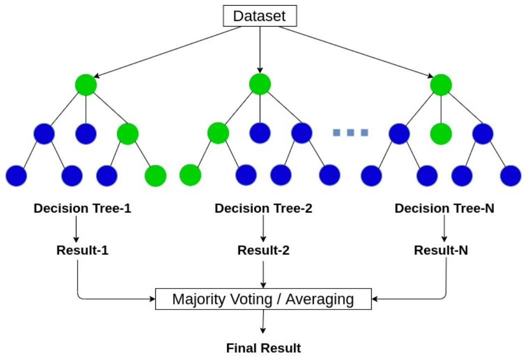

Figure 2. Visualisation on how random forest utilises decision trees,(Ampadu, 2021).

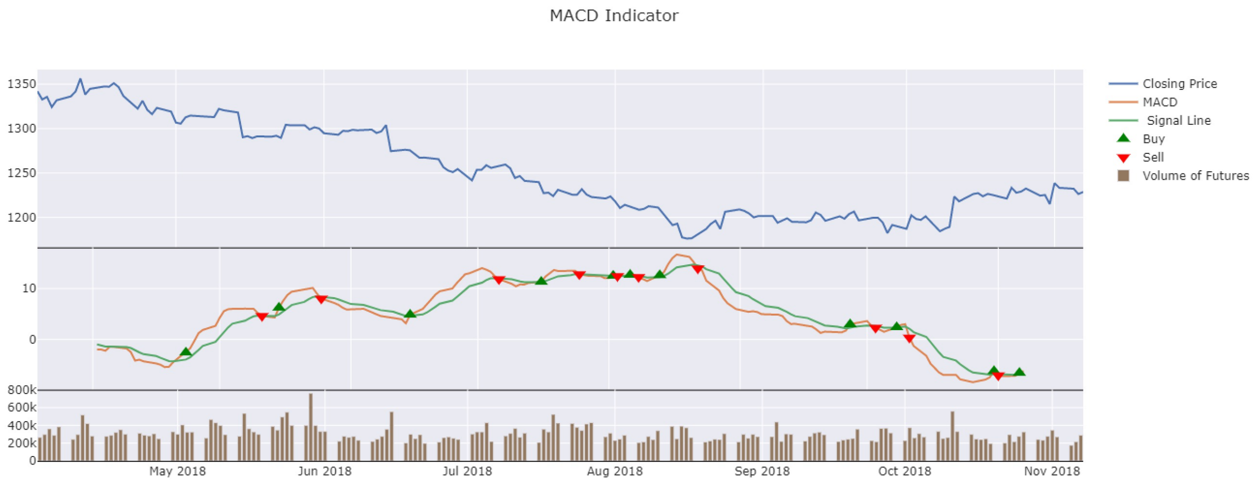

Figure 1. A chart which shows trigger signal from the MACD (26/12) as well as a histogram.

Method

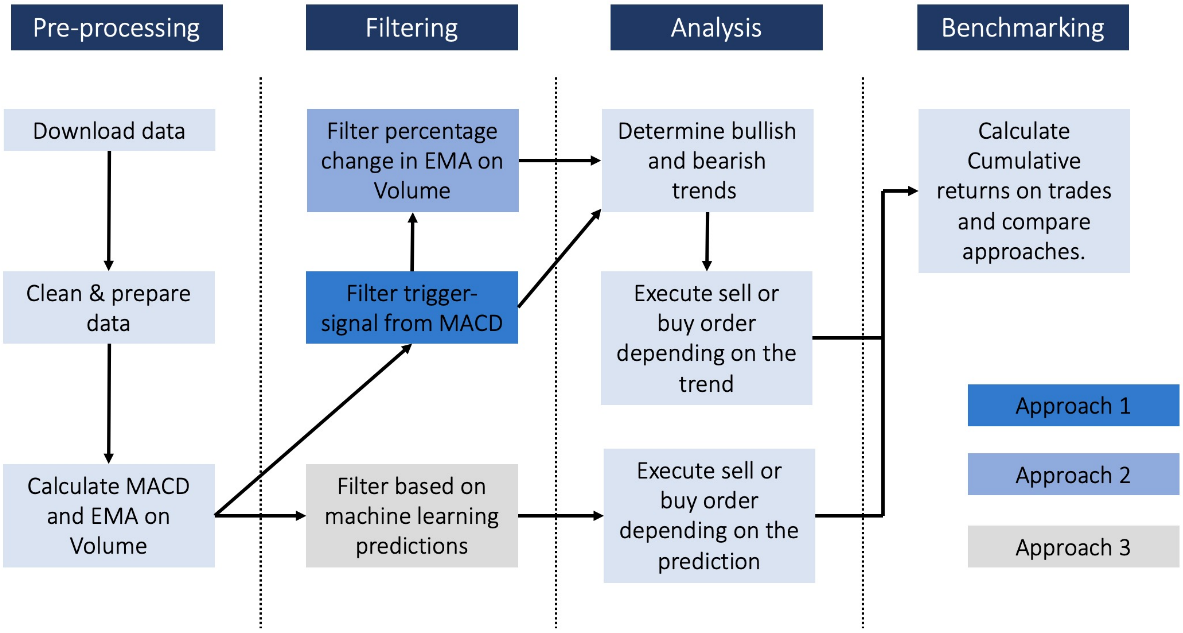

Figure 3. A flowchart to show our trading algorithm and the difference between approaches in our project.

To analyse momentum strategies and machine learning, three different approaches will be compared to each other over three different time periods, short, medium- and long-term. The utilisation of MACD on the different time periods has been divided into the following criteria 12/26, 40/80, and 120/160. The first approach (base strategy) consists of solely using MACD's trigger signals and depending on if the trend is bearish or bullish the algorithm will buy or sell.

While the second approach combines MACD with a condition on the percentage change of the EMA of total volume. This will be done by first filtering out the signals we get from only using the MACD and then calculating the EMA of the total traded volume on the commodity then the percentage change of the EMA will be calculated. This allows the algorithm to filter out the MACD trigger signals which satisfies our criteria on the percentage change of the volume. The time periods of the EMA is defined as 20, 30, and 40 days-period. The goal of the approach is to take into account how other professional and institutional traders react to the market. The third approach goal is to see if a machine-learning algorithm as Random Forest can beat traditional trading strategies by using the same data. Hence the machine learning features will be identical to approach two's input. Because random forest is a supervised algorithm, the output will be defined as if the past five changes in closing price are positive then we buy the commodity.

Since the machine learning model needs to be trained on data, we have used approximately 25% of the data for training and the rest for prediction. Hence all approaches will cover the period 2009-04-01 to 2021-11-01.

The different approaches have been implemented in Python and will be tested on the collected data. To be able to compare differences and similarities between the approaches and the different commodities, cumulative returns, win-loss ratio, total trades, and average return will be calculated.

	Description	MACD	Change in Volume	Volume Criteria
Approach 1	MACD	Yes	No	No
Approach 2	MACD- Volume	Yes	Yes	Yes
Approach 3	Machine learning	Yes	Yes	No

Table 1. A table that shows which indicators are used per Approach.

Results

Time period	Approach	Benchmark	Agricultural Commodities	Energy Commodities	Metal Commodities	Total
Short-Term	MACD	Win ratio (%)	67.28%	64.04%	65.74%	65.69%
		Cumulative Returns (%)	4.83%	-17.79%	14.10%	0.38%
		Average Number of Trades	129.00	125.00	125.67	126.56
	MACD- Volume	Win ratio (%)	53.76%	57.50%	67.84%	59.70%
		Cumulative Returns (%)	12.09%	66.13%	69.99%	49.40%
		Average Number of Trades	17.25	13.50	18.67	16.47
	Machine Learning	Win ratio (%)	43.88%	41.84%	45.98%	43.9%
		Cumulative Returns (%)	36.83%	29.59%	17.50%	27.97%
		Average Number of Trades	180.75	138.00	231.33	183.36
Medium-Term	MACD	Win ratio (%)	67.36%	67,92%	70,87%	68.72%
		Cumulative Returns (%)	-4.97%	-0.21%	65.15%	19.99%
		Average Number of Trades	46.25	48.50	52.20	48.98
	MACD- Volume	Win ratio (%)	55.99%	66.67%	59.13%	60.60%
		Cumulative Returns (%)	52.38%	-34.47%	76.58%	31.50%
		Average Number of Trades	9.50	10.00	12.00	10.50
	Machine Learning	Win ratio (%)	45.58%	40.46%	48.87%	44.97%
		Cumulative Returns (%)	83.15%	75.07%	111,10%	89.77%
		Average Number of Trades	144.75	160.00	130.20	144.98
Long-Term	MACD	Win ratio (%)	64.93%	71.36%	70.88%	69.06%
		Cumulative Returns (%)	16.10%	-6.65%	58.09%	22.51%
		Average Number of Trades	34.25	36.50	39.20	36.65
	MACD- Volume	Win ratio (%)	68.75%	65.00%	57.33%	63.69%
		Cumulative Returns (%)	291.80%	-15.11%	71.01%	115.90%
		Average Number of Trades	4.75	3.50	5.60	4.62
	Machine Learning	Win ratio (%)	47.82%	57.53%	45.70%	50.35%
		Cumulative Returns (%)	77.08%	-2.01%	77.60%	50.89%
		Average Number of Trades	76.25	47.00	63.00	62.08

Table 2. Summary of main results, split into the different commodity groups.

General Results

In this section, the result of the base strategy of using MACD is compared with MACD- volume and the ML approach across three time periods. Table 2 presents the average win ratio, average cumulative returns, and an average number of trades across different commodity categories. These benchmarks allow us to evaluate the gains from different approaches and how they yield on different commodity groups.

Results

First analysing across different periods, it can be noted that the average win-loss ratio is above 50 percent for the MACD approach and the MACD with volume approach. This is a good signal as a win-loss ratio of above 50 percent is considered favourable as the algorithms are winning more trades than the losses. However, the ML algorithm has a lesser win-loss ratio as compared to the other traditional approaches. But, the ML algorithm results in higher cumulative returns compared to the traditional MACD strategy.

Results

In fact, as seen in Table 2, the ML algorithm delivers the highest average cumulative return of 89.77% in the medium-term time periods and trails behind the MACD-Volume approach in the short-term and long-term. The MACD with volume algorithm performs best as it delivers the highest cumulative returns in two out of three periods (both the short and long-term). The total number of trades as expected is high during the short-term and is low for the long term. Across all the time periods, the ML algorithm has the largest number of total trades followed by the MACD algorithm. The MACD with volume algorithm has a very low number of total trades and this may be due to the volume constraint which is imposed on it.

Now, taking a closer look within each time period yields some interesting results. In the short-term, it can be noted that the MACD with volume strategy achieves the highest cumulative returns for both metals and energy commodities. The ML strategy delivers the highest return for agricultural commodities and trails behind the MACD volume in the other categories. For energy commodities, unlike the traditional MACD, both the strategies created here (ML and MACD-Volume) deliver positive cumulative returns.

Similar trends can be noticed in the medium-term as here too, the MACD with volume approach delivers the highest cumulative returns for both metal and energy commodities. The ML approach again performs the best for agricultural commodities.

In the long-term, there are slight changes in the trend as, unlike the previous time periods, MACD with volume trails behind ML strategy in both energy commodities and metals (only slightly behind). However, MACD-volume fetches the highest cumulative return for agricultural commodities this time by beating the ML approach. Notably, all the strategies deliver negative cumulative returns for the energy commodities. This can be an important finding as long trading of energy commodities such as crude oil and natural gas may not be profitable.

Overall, it can be seen that the approaches created in this paper beat the base strategy of using MACD across various commodity groupings. In spite of having a low number of trades, the MACD with volume approach appears to be the best for energy and metal categories in the medium-term. Similarly, the ML strategy performs the best for agricultural commodities in the short and medium periods. Long-term trading gives mixed results, with long-term energy trading being unprofitable.

For commodity-wise results

Since a large number of commodities have been considered, it is hard to present the results for each and every commodity. Thus, in this section, results for only four popular commodities which are traded in high volumes in their respective categories are presented in Table 3. For the results for the other commodities, please refer to the appendix.

The selected commodities that are presented here are copper, gold, wheat and crude oil. While looking at copper, we find that the traditional MACD algorithm gives the highest cumulative returns for short and long time periods. Additionally, the highest return for copper is achieved during long-term trading. The MACD with volume for this commodity gives the least returns as it is affected by the high average loss.

Gold offers some interesting results as the ML approach delivers the highest return in the medium and long-term. The highest return for gold is achieved during the medium-term when the ML algorithm is used. However, the MACD volume algorithm also results in the highest cumulative returns for the short-term.

Results

Time period	Approach	Benchmark	Copper	Gold	Wheat	Crude Oil
Short-Term	MACD	Win ratio (%)	70.45%	65.08%	65.19%	-65.00%
		Cumulative Returns (%)	36.88%	-8.17%	-24.33%	-50.16%
		Number of trades	132	126	135	120
	MACD- Volume	Win ratio (%)	66.67%	77.78%	58.82%	75.00%
		Cumulative Returns (%)	2.21%	85.52%	133.30%	82.14%
		Number of trades	12	18	17	12
	Machine Learning	Win ratio (%)	38.71%	50%	36.82%	45.75%
		Cumulative Returns (%)	-31.43%	12.37%	-18.64%	69.57%
		Number of trades	272	246	239	247
Medium-Term	MACD	Win ratio (%)	71.43%	66.67%	60.47%	72.00%
		Cumulative Returns (%)	13.40%	2.81%	-21.98%	-13.80%
		Number of trades	56	42	43	50
	MACD- Volume	Win ratio(%)	45.45%	50%	37.60%	75%
		Cumulative Returns (%)	5.17%	11.26%	-4.13%	6.13%
		Number of trades	11	10	8	8
	Machine Learning	Win ratio (%)	45.95%	54.55%	41.67%	45.21%
		Cumulative Returns (%)	53.68%	117.40%	154.76%	188.28%
		Number of trades	74	110	60	292
Long-Term	MACD	Win ratio (%)	63.89%	77.78%	65.79%	74.29%
		Cumulative Returns (%)	38.05%	19.38%	-14.49%	-10.24%
		Number of trades	36	36	38	35
	MACD- Volume	Win ratio (%)	66.67%	33.33%	66.67%	50.00%
		Cumulative Returns (%)	-30.22%	-31.90%	61.83%	-10.72%
		Number of trades	3	3	3	2
	Machine Learning	Win ratio (%)	48.00%	58.06%	53.06%	55.06%
		Cumulative Returns (%)	35.71%	79.85%	33.65%	20.37%
		Number of trades	75	52	49	89

Table 3. Summary of results on copper, gold, wheat and crude oil.

For wheat, the ML algorithm beats all the other strategies in all medium and long time periods we have considered. Medium trading of this commodity gives the highest return of (154.8%) while using the ML algorithm. The MACD algorithm doesn't work well for this commodity as we see negative returns in all time periods.

For crude oil, the ML algorithm beats the other algorithms in the medium and long-term. In the long-term, the ML algorithm gives the highest return (188.28%). In the long-term, all the strategies except ML give negative returns thus strongly suggesting long-term trading of this commodity. The MACD approach works particularly badly for crude oil as it always results in negative returns regardless of the selected time period.

Results & Analysis

Analysis of this report's approaches compared to buy- and hold

In Table 4 the return of solely buying and selling the commodity once during the time frame has been calculated. The following results were calculated: agricultural commodities with 88,88%, energy commodities with 56.53%, and lastly metal commodities with 219.38%. Notably, for metal commodities rather high return was an effect of the high return on palladium which was 793.64%. The average annual standard deviation in percentual return per commodity tells how the volatility per commodity type is. Regarding energy commodities, the standards deviation is rather high compared to the other commodities, and the total return for the buy- and hold result is 56.53%. Generally, this report's approaches seem to have a problem with the high volatility, and six out of nine approaches get a negative result. The longer the time period the more losses the approaches get.

Metal commodities show a lower rate of volatility i.e standard deviation of 18,96% and the majority of the approaches get a cumulative result of around 60-70% compared to the buy- and hold which is 219.38%. Worth mentioning is the case of the high return on palladium and how our approaches lose a lot compared to buy- and hold the commodity. The highest cumulative return was 370,25% for approach MACD-volume medium-term. Although the approach's cumulative result performs as well as to just buy- and hold the win ratio is higher than the other commodities which could be an indication that momentum strategies work better on commodities with lower volatility.

Commodity group	Agricultural	Energy	Metal	Metal excluding palladium
Average annual standard deviation	22.70%	32.96%	18.96%	17.72%
Buy- and hold	88.88%	56.33%	219.38%	75.82%

Table 4. Table that shows average annual standard deviation of percentual change in closing price and the result from buy- and hold.

Analysis

Approach 1 - MACD

From Table 2 it becomes clear that our MACD algorithm (base strategy) has the best win-loss ratio for almost all the cases (approximately 60-70%). Even though the win-loss ratio varies, the average losses per trade are bigger than the average wins. Independent of the time period, MACD seems to work best on the commodity group metals.

Approach 2 – MACD with Volume criteria

The goal in Approach 2 was to tweak the conventional MACD, by combining it with the changes in traded volume. This, thus captures the market reaction to changes in traded volume. From Table 2 it becomes clear that the approach MACD with volume beats approach 1 in total cumulative returns in all time periods. The main difference with approach 1 is that combining volume with MACD leads to few trades and a lower win-loss ratio. Referring to Table 3 and the appendix the main weakness for approach 2 seems to be the difference between average win-loss per trade as the loss mostly is bigger than the win. For the long-term, this approach became too strict with the condition on volume as, during the period, there were only 2-3 trades per commodity.

Approach 3 – Machine learning

Here, the goal was similar to the other approaches but instead of setting relatively hard conditions, the ML algorithm uses the relations between the data. As it can be seen from Tables 2 and 3, this approach led to a higher number of trades and an overall positive result. Approach 3 seems to work best during the medium-term and what's interesting is that the win-loss ratio is below 50% and yet the cumulative return is the highest compared to the other approaches. This has to do with the fact that unlike the other approaches which had a high win-loss ratio but high losses per trade, the ML algorithm is the opposite.

Conclusion

The MACD and MACD-volume both had strong win-loss ratios but had problems in foreseeing bearish trends as the average losses kept the cumulative return down. Our hypothesis that the combination of MACD and volume would better capture the market wasn't entirely as expected. Compared to the base strategy of using MACD, the MACD-volume had a lower win-loss ratio but the average win and losses increased. Ultimately this probably has to do with the harsh criteria for a sell or buy signal to get triggered. However, there were cases when the MACD with volume performed better than solely using MACD and thereby making it interesting for further investigation on how to make the combination work. Besides finding ways to cut losses, it's also worth looking into possibilities to get a higher number of trades. This could be done by changing the volume criteria for example that the volume criteria should be met for the past five days and not only on the same day as the MACD trigger. Furthermore, some sort of weighting of different indicators could be done depending on what the algorithm deems to be the strongest indicator.

On the whole, the ML approach proved to be a powerful tool when investing and out-performed the other two approaches for a number of cases as for example the medium-term. Despite the fact that the ML approach had a lower win-loss ratio it made up for it by having a higher number of trades with generally a lower average loss per trade. Bear in mind that the optimization of the approach was minimal as this report only sought to test how the results may defer from only using the same indicators as the other approaches i.e. MACD and the percentage change of volume. One important key-point from this is that rather than setting quite hard criteria's as in traditional strategies, a powerful strategy could be created by finding correlation and classifying the data as in the ML algorithm. This conclusion can be drawn from the fact that the machine learning approach didn't seem to have the same weaknesses as the more traditional approaches with cutting it loses. Instead of relying on hard criteria's, the ML model seemed to react faster as shown by the higher number of trades. Additionally, the machine learning model shows potential and improvements could be done by adding new features as other indicators and experimenting with the set target when training the model.

To summarise, we get mostly positive results and rather a high win ratio when implementing momentum strategies. The results vary a lot depending on the approach, commodity, and selected time period but it shows the potential of using momentum strategies when trading commodities. Although further optimization could be done, by improving the approaches by foreseeing negative trends and by building a more effective ML model. A particular strategy cannot be singled out as the results vary across time periods and commodity types. Finally, this report shows that momentum strategies can be an effective trading tool when investing future contracts on commodities.

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Approach	Benchmark	Copper	Corn	Crude oil	Gold	Lumber	Natural gas	Palladium	Platinum	Silver	Soybean	Wheat
MACD	Win ratio (%)	70,45%	69,85%	65,00%	65,08%	64,49%	63,08%	70,71%	62,60%	61,11%	69,57%	65,19%
	Cumulative Returns (%)	36,88%	17,81%	-50,16%	-8,17%	-24,10%	14,59%	176,60%	-61,05%	-35,56%	49,93%	-24,33%
	Average win	8,32	13,95	3,2	24,97	12,23	0,18	37,58	31,09	0,72	31,1	18,21
	Average loss	-16,96	-28,82	-5,79	-41,7	-53,89	-0,26	-56,86	-68,82	-1,25	-56,22	-35,06
	Number of trades	132	136	120	126	107	130	140	123	126	138	135
MACD-Volume	Win ratio (%)	66,67%	52,63%	75,00%	77,78%	61,90%	40,00%	69,57%	70,00%	61,11%	41,67%	58,82%
	Cumulative Returns (%)	2,21%	-46,36%	82,14%	85,52%	-31,48%	50,12%	241,96%	38,49%	83,24%	-7,09%	133,30%
	Average win	12,79	32	11,62	89,38	24,65	0,96	67,08	97,04	3,12	47,1	67,6
	Average loss	-23,27	-58,89	-23,03	-105,55	-54,89	-0,41	-50,26	-130,88	-2,04	-41,18	-28,96
	Number of trades	12	19	12	18	21	15	23	20	18	12	17
Machine Learning	Win ratio (%)	38,71%	45,67%	45,75%	50,00%	48,74%	37,93%	53,66%	36,92%	47,87%	44,30%	36,82%
	Cumulative Returns (%)	-31,43%	113,26%	69,57%	12,37%	8,38%	-10,40%	150,30%	-41,20%	6,58%	44,33%	-18,64%
	Average win	9,23	14,62	1,79	20,1	15,74	0,13	23,61	35,53	0,61	47,99	22,26
	Average loss	-6,86	-8,2	-1,46	-18,68	-17,37	-0,1	-21,16	-25,16	-0,52	-31,41	-13,48
	Number of trades	272	127	247	246	199	29	246	214	211	158	239

Table 5. Table that show returns divided per commodity for short-term.

Approach	Benchmark	Copper	Corn	Crude oil	Gold	Lumber	Natural gas	Palladium	Platinum	Silver	Soybean	Wheat
MACD	Win ratio (%)	71,43%	66,67%	72,00%	66,67%	77,08%	63,83%	81,48%	73,08%	61,70%	65,22%	60,47%
	Cumulative Returns (%)	13,40%	1,09%	-13,80%	2,81%	33,27%	13,39%	214,45%	86,64%	8,47%	-32,27%	-21,98%
	Average win	12,88	24,26	4,1	40,05	35,09	0,3	54,04	50,72	1,15	44,41	30,95
	Average loss	-24,39	-44,34	-12,46	-68,92	-138,46	-0,39	-149,18	-99,24	-1,87	-11,55	-39,47
	Number of trades	56	48	50	42	48	47	64	52	47	46	43
MACD-Volume	Win ratio (%)	45,45%	54,55%	75,00%	50,00%	81,82%	58,33%	69,23%	66,67%	64,29%	50,00%	37,60%
	Cumulative Returns (%)	5,17%	62,23%	6,13%	11,26%	186,52%	-75,06%	354,47%	-24,93%	36,93%	-35,11%	-4,13%
	Average win	52,96	116,62	7,41	90,88	112,62	0,3	180,39	68,5	2,23	35,62	108,25
	Average loss	-38,91	-87,15	-33,44	-6956	-437,2	-2,24	-57,24	-251,92	-2,84	-169,44	-76,1
	Number of trades	11	11	8	10	11	12	13	12	14	8	8
Machine Learning	Win ratio (%)	45,95%	43,92%	45,21%	54,55%	49,02%	35,71%	54,30%	35,24%	54,29%	47,71%	41,67%
	Cumulative Returns (%)	53,68%	82,97%	188,28%	117,40%	73,33%	-38,14%	360,54%	-34,22%	58,08%	21,53%	154,76%
	Average win	16,56	13,46	2,33	39,95	16,3	0,12	37,07	26,26	0,46	22,09	36,82
	Average loss	-10,7	-7,39	-1,66	-27,81	-11,75	-0,18	-33,41	-20,13	-0,29	-17,93	-13,71
	Number of trades	74	148	292	110	153	28	291	105	71	218	60

Table 6. Table that show returns divided per commodity for medium-term.

Approach	Benchmark	Copper	Corn	Crude oil	Gold	Lumber	Natural gas	Palladium	Platinum	Silver	Soybean	Wheat
MACD	Win ratio (%)	63,89%	65,79%	74,29%	77,78%	74,29%	68,42%	76,19%	69,05%	67,50%	53,85%	65,79%
	Cumulative Returns (%)	38,05%	12,63%	-10,24%	19,38%	102,07%	-3,06%	215,39%	14,76%	2,87%	-35,83%	-14,49%
	Average win	18,89	30,56	5,1	50,32	35,25	0,25	81,31	53,07	1,38	59,39	32,55
	Average loss	-18,1	-48,58	-17,08	-112,76	-132,29	-0,54	-48,8	-112,91	-2,54	-112,94	-42,56
	Number of trades	36	38	35	36	35	38	42	42	40	26	38
MACD-Volume	Win ratio (%)	66,67%	83,33%	50,00%	33,33%	75,00%	80,00%	70,00%	50,00%	66,67%	50,00%	66,67%
	Cumulative Returns (%)	-30,22%	1065,75%	-10,72%	-31,90%	38,89%	-19,49%	370,25%	-46,83%	93,76%	0,74%	61,83%
	Average win	17,17	72,6	37,25	23,9	29,38	0,27	307,78	91,27	4,39	79,75	221,12
	Average loss	-127,65	-23	-45,7	-270,8	-101,2	-3,32	-43,67	-412,4	-1,67	-48,75	-152,5
	Number of trades	3	6	2	3	8	5	10	6	6	2	3
Machine Learning	Win ratio (%)	48,00%	43,37%	55,06%	58,06%	42,86%	60,00%	48,15%	35,29%	39,00%	52,00%	53,06%
	Cumulative Returns (%)	35,71%	57,95%	20,37%	79,85%	122,83%	-24,38%	253,60%	-8,53%	27,39%	93,88%	33,65%
	Average win	8,097	17,78	2,97	61,31	18,84	0,46	140,6	87,61	1,4	33,7	18,18
	Average loss	-5,5	-9,43	-2,97	-50,7	-8,81	-1,05	-43,82	-48,51	-0,86	-15,98	-12,45
	Number of trades	75	83	89	52	98	5	27	61	100	75	49

Table 7. Table that show returns divided per commodity for long-term.

Commodity	Copper	Corn	Crude oil	Gold	Lumber	Natural gas	Palladium	Platinum	Silver	Soybean	Wheat
Average annual standard deviation	17,83%	21,47%	29,02%	12,43%	29,40%	36,91%	23,93%	17,59%	23,02%	17,01%	22,93%
Buy and hold	136,24%	43,50%	72,70%	92,62%	235,18%	40,35%	793,64%	-10,17%	84,58%	29,81%	47,05%

Table 8. Table that show average annual standard deviation and the results for buy- and hold divided per commodity.

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Other