

## Seasonality in Commodities Market: The SeasonAlgo Strategy.

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**Abstract:** Seasonality in the prices of commodities has been largely discussed, in both the academic and practical field. The extent to which this was studied lead to an algorithm, made available to the public, available on the SeasonAlgo website. This algorithm tracks seasonal patterns in commodities prices, allowing traders to find periods with repeating patterns that can be exploited for profits. This paper will analyze this active strategy, and how it fares against passive trading, which has been found to be the most profitable in the long run.

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## Introduction

The Efficient Market Hypothesis (EMH), introduced by Professor Eugene Fama, argues that stock always trade at its fair value, making it impossible for investors to either purchase undervalued stocks or sell stocks at inflated prices. A direct implication of this hypothesis is that prices fully reflect all available information, thus prices should only react to news, which is by definition, random. The EMH correlates with a phenomenon known as the Random Walk Hypothesis. This hypothesis argues that stock market prices follow a random walk, making it rather unlikely to predict any future outcomes. Investors and researchers have disputed over the EMH empirically and theoretically for decades. Various academics have proved the price inefficiency in agricultural commodity markets (Bigman et al., 1983; Hunt, 1974 and Helms et al., 1984), however Garcia et al. attempted to further analyse the arguments raised by the abovementioned individuals (1988). Based on these studies, an algorithm was constructed in order to track past seasonal patterns. In addition, this algorithm, available at SeasonAlgo.com, can also be used to search for profitable trade opportunities. This study focusses on and intends to analyse results obtained from suggested trades, ranging from 1995 to 2014, and comparing the findings to buy-and-hold strategies. Commodities under investigation include those from ICE, CBOT and COMEX markets as well as strategies ranging from single contracts to intercommodity and intracommodity spreads.

## The Strategy

The SeasonAlgo algorithm examine entry and exit dates combinations in 3 or 6 month window price variations, in search for a pattern that can be traded for profits. This algorithm can also filter out those patterns with higher win rates over a desired time period. For the sake of this study, strategies with more than 90% win rates over the past thirty years were selected. This means that for every thirty trades, only three trades ended up in a loss. However, this is a self adjusted strategy, which means that if a 90% win rate strategy is not profitable in one year, the algorithm will filter it out in the next year. This is due to the fact that it will not fit the 90% win rate parameter as stated earlier. To replicate this strategy, one can go into SeasonAlgo website ([www.seasonalgo.com](http://www.seasonalgo.com)) and, at the “search” tab, use the filter 90% win rate over 30 years. The presented strategy uses a settle price of the opening and closing days. If the entry day falls on a weekend or on a public holiday, it is postponed. However, if falls on the closing day, it will be anticipated. This means that the operation should fall inside the time frame presented by the algorithm. In this study, 15 892 trades were suggested by the algorithm, 65% of which were profitable, with an average profit of USD 529,31, amassing a total of U\$ 8,411,769.56 in profits as shown in the table 1. All of the trades can be found in a spreadsheet whose link for download is at the end of this work.

Table 1: Results of the trades suggested by the SeasonAlgo algorithm from 1995 to 2015

## Summary

	Result	Avg	#	Win #	Loss #	win%	Avg Win
1995-2014	\$8.411.769,56	\$529,31	15892	10369	4863	65%	\$1.304,70
	Avg Loss	Best	Worst	STDev	VaR	Max DD	
	-\$1.052,16	\$56.200,15	-\$23.299,96	\$3.844,89	-\$7.006,68	\$734.428,62	

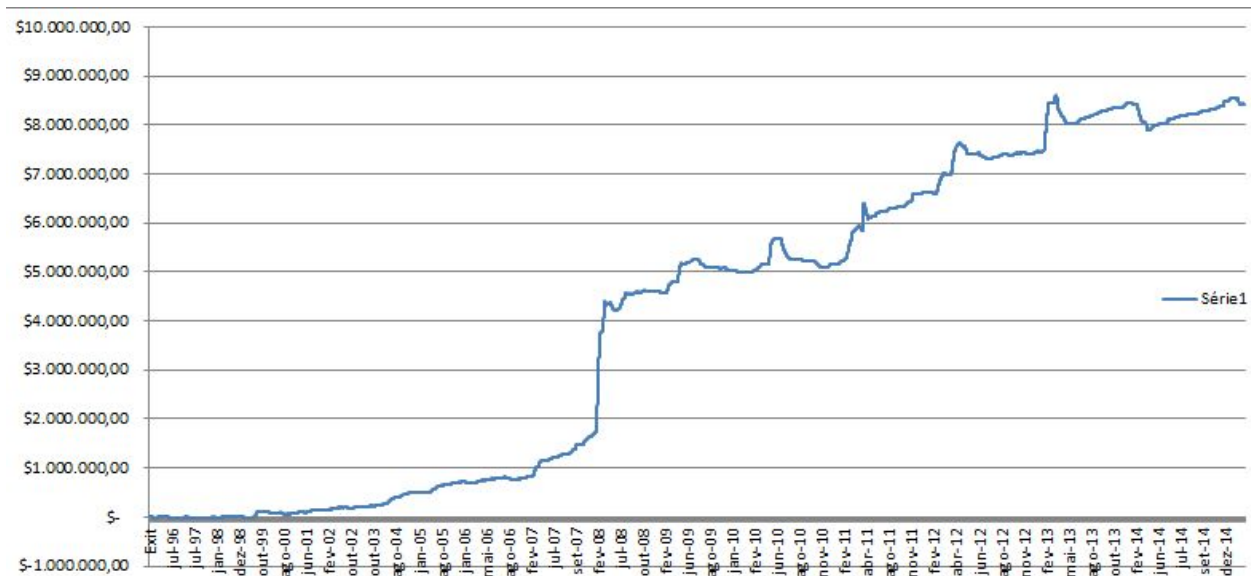


Figure 1: Capital evolution of the presented strategy.

## Outright Futures

Outright futures position is a long or short trade on an underlying futures contract that has the potential for unlimited profit, but also carries the risk of unlimited losses. It is also referred to as naked futures due to the fact that they leave the investor highly exposed to prices variations, since it buys just a single contract. To reduce risk, the investor may choose to purchase a spread position.

## Spreads

Spread can be defined as the difference in price between related securities and can be traded by simultaneously purchasing and selling related securities known as legs. This is done in an attempt to gain a profit from the widening or narrowing of the price difference, rather than from the movement in the prices of the legs directly. In this study two types of spreads are used namely intracommodity spreads, also referred to as calendar spreads, and intercommodity

spreads. Calendar spreads are executed with legs differing only in delivery date. It is the market expectation of supply and demand at one point in time relative to another point in time, i.e March coffee relative to May coffee. Since these are different deliveries of the same contract, they can also be referred to as intracommodity spreads. Intercommodity spreads are formed based on two distinct but interrelated commodities reflecting the economic relationship between them, i.e gold and silver spread, and crack spread which is the spread between the price of crude oil and the price of one of its byproducts. Margin requirements for future spreads are usually less than the requirements for the outright positions. This is due to the lower volatility of future spreads relative to the volatility of individual legs with regards to the change in market fundamentals of a commodity, which will affect both legs in a similar manner. Spreads are either “purchased” or “sold”, depending on whether the trade will profit from the widening or narrowing of the spread. If the trader suspects that the spread between March and May coffee will narrow, he will, in effect, buy the March contract and sell the May contract. This works because when the spread narrows, either the price of the first leg went up more than the aftermost did, or the price of the second leg fell more than the aftermost did.

## Results

Since commodity markets are individual and distinctive with unique characteristics that vary depending on the contract, finding a benchmark for this study proved to be a challenging task. Thus, we decided to sort the results based on the category of commodities, using a strategy of buying and holding the group of commodities in each category as our benchmark to observe if the algorithm beats a passive strategy. The risk measure used in order to compare the strategies to each other was VaR, since the price variations cannot be compared due to the fact that contract sizes vary. VaR is defined as a threshold loss value, such that the probability that the loss on the portfolio over the given time horizon exceeds this value is  $p$ . In this study we used the 5% VaR, which means there is a 5% chance that the portfolio get losses higher than the shown VaR value. The horizon's of the benchmark varies as well, depending on the number of trades suggested by the algorithm per period in each category. In some categories we used the weekly price variations of the commodities, whereas in others daily and monthly variations were used.

## Energy

The algorithm suggested 395 trades between 03/11/2009 and 05/09/2015, in contracts of GasOil, Heating Oil and Crude Oil. For the benchmark we used the sum of the weekly returns of the three contracts. By comparing table 2.1 and 2.2 it was observed that the seasonal strategy presents lower VaR percentages, average loss and higher win percentages. However, the results for this specific category are not promising due to the high drawdown and losses. As shown in the accumulated capital chart in figure 2, the losses observed between February and June 2012, as well as those taken in April and May 2013 can be attributed to outright positions in Heating Oil and GasOil futures. If the outright positions are excluded and only the spread

trades are left, the results are promising, wielding a higher profit and win rate, and lower VaR and Drawdown, as shown in table 2.3.

**Table 2.1:** results of the SeasonAlgo algorithm (source: [www.seasonalgo.com](http://www.seasonalgo.com)).

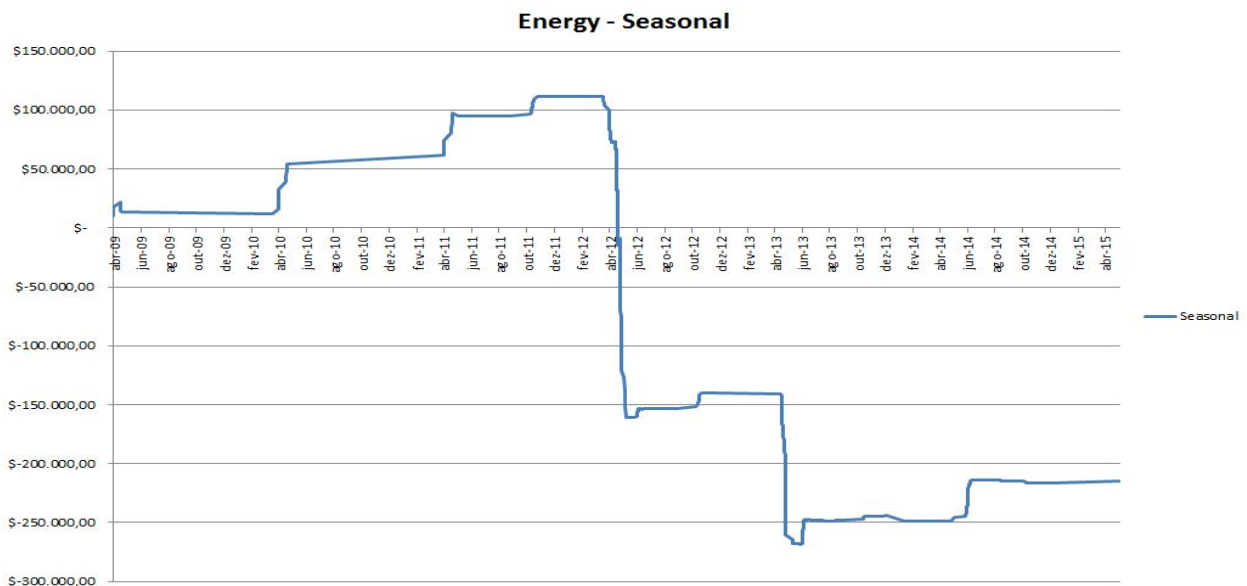
Energy - Seasonal					
Resultado	Avg	#	Win #	win%	Avg Win
\$ -215.164,53	\$ -544,72	395	232	59%	\$ 942,26
Avg Loss	Best	Worst	STDEV	VaR	MAX DD
\$ -2.780,56	\$10.214,37	\$-15.733,22	\$2.924,04	\$ -6.275,84	\$380.039,50

**Table 2.2:** results of the buy and hold strategy (source: [www.quandl.com](http://www.quandl.com)).

Energy Buy and Hold					
Resultado	Avg	#	Win #	win%	Avg Win
\$ 48.282,60	\$ 150,88	320	164	51%	\$ 6.855,54
Avg Loss	Best	Worst	STDEV	VaR	MAX DD
\$ -6.897,60	\$26.886,00	\$-44.474,20	\$8.947,70	\$-17.386,60	\$195.066,00

**Table 2.3:** results of SeasonAlgo algorithm filtered by spread positions only (source: [www.seasonalgo.com](http://www.seasonalgo.com)).

Seasonal - Energy - Spread Only					
Resultado	Avg	#	Win #	win%	Avg Win
\$ 61.008,73	\$ 212,57	287	213	74%	\$ 501,69
Avg Loss	Best	Worst	STDEV	VaR	MAX DD
\$ -684,36	\$1.726,20	\$-4.656,82	\$ 735,85	\$-1.229,69	\$4.656,82



**Figure 2:** capital evolution chart for SeasonAlgo strategy in energy category

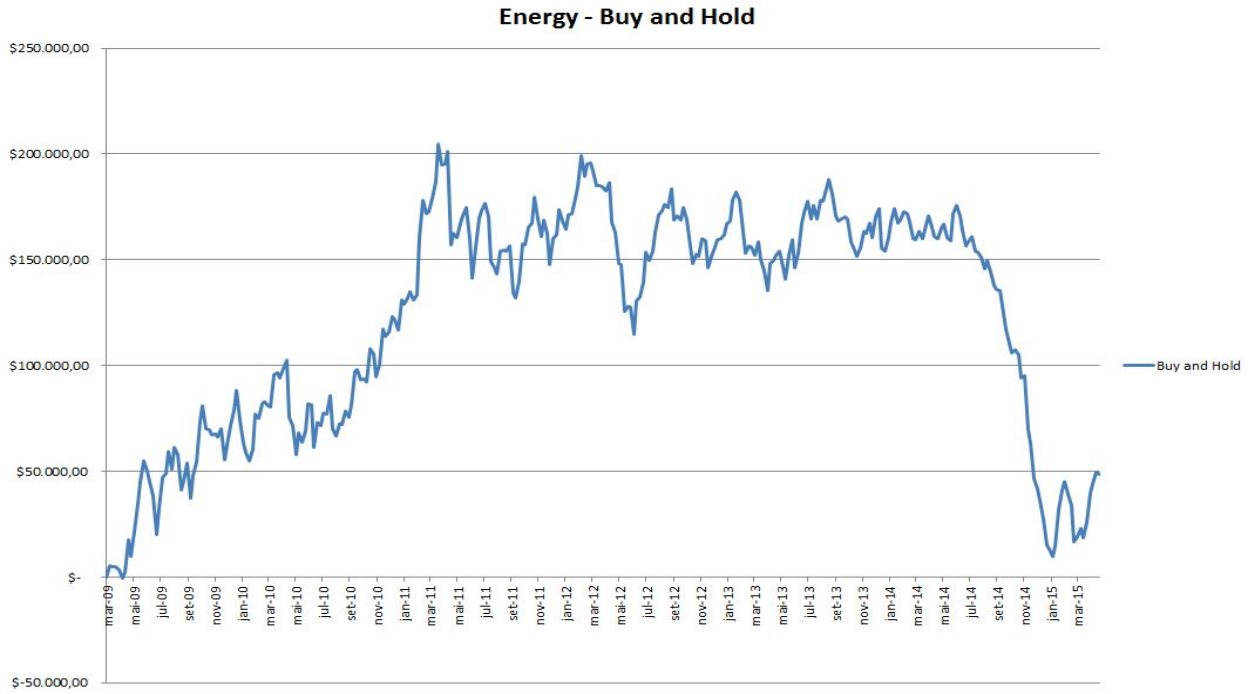


Figure 3: capital evolution chart for buy and hold strategy in energy category

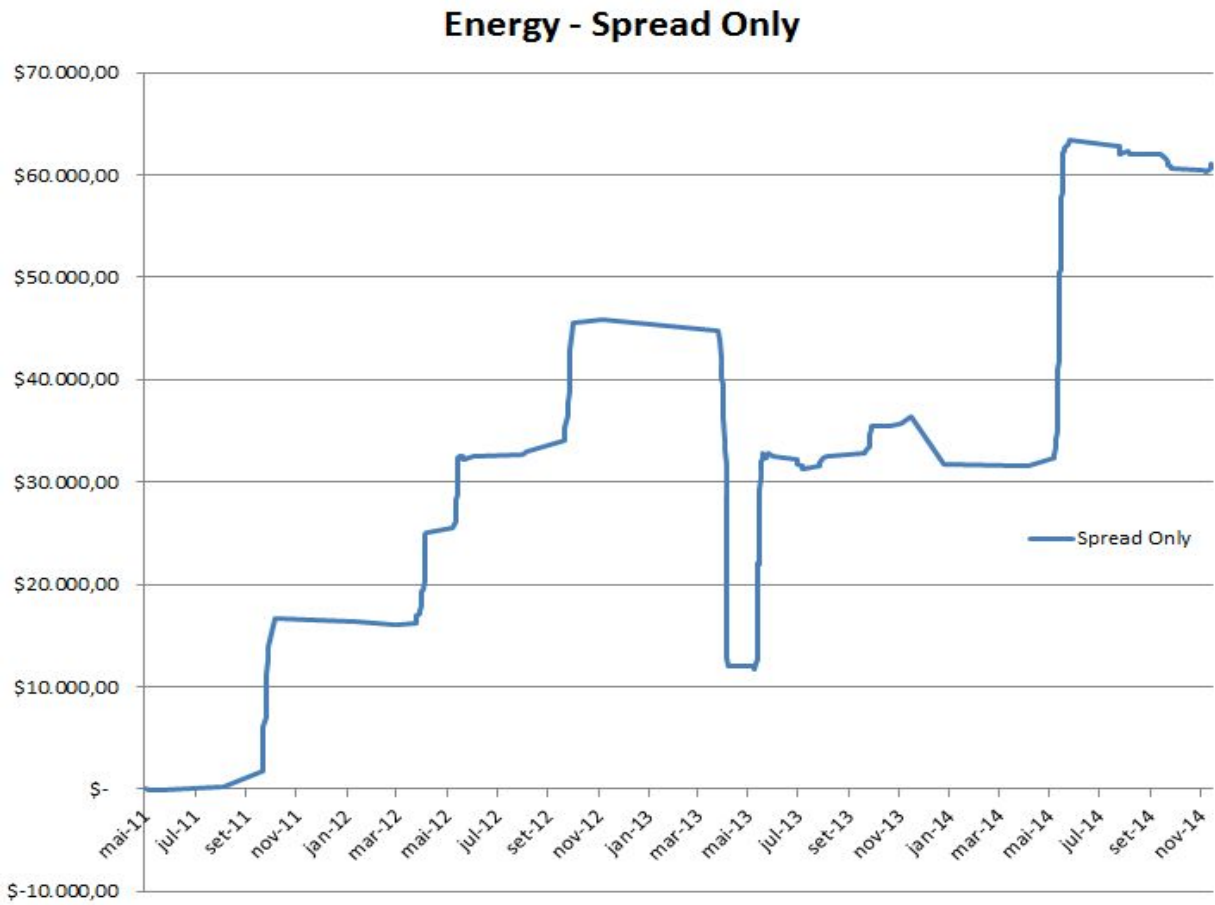


Figure 4: capital evolution chart for SeasonAlgo strategy in energy category - Spread only positions



## Currency

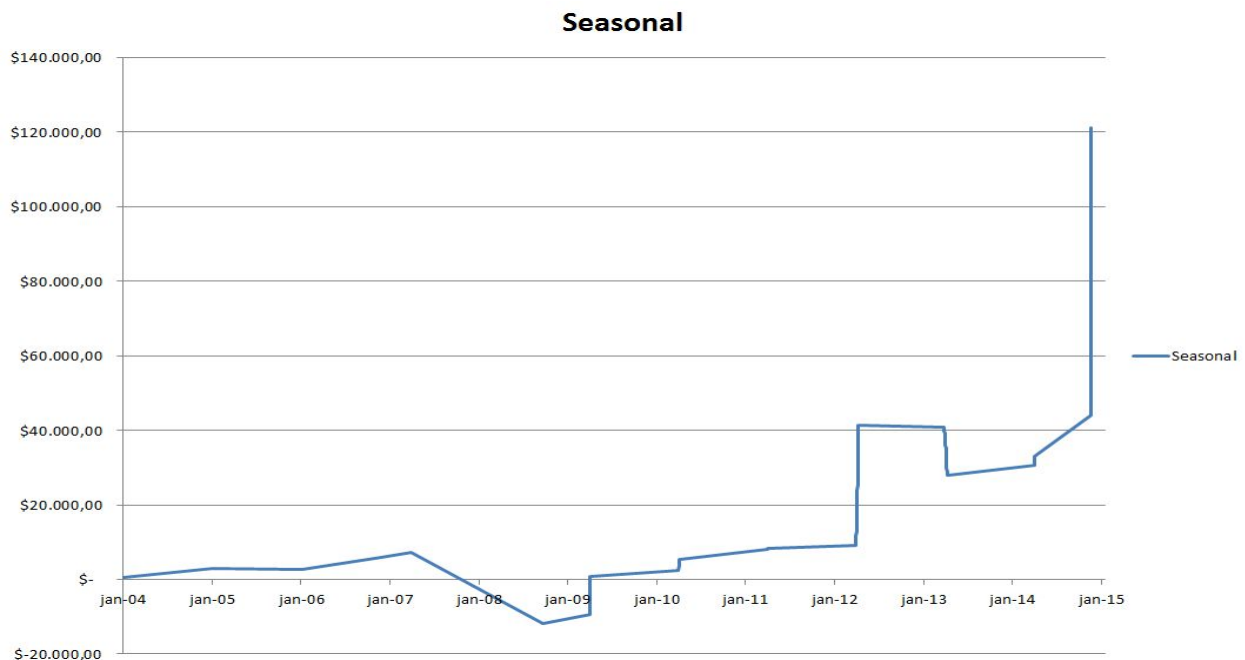
The algorithm suggested 39 trades between 01/05/2004 and 12/06/2014, in contracts of Canadian Dollar, Euro, British Pounds, Japanese Yen and Swiss Franc. For the benchmark we used the sum of the monthly returns of the five contracts against the US dollar. The SeasonAlgo strategy beat the market by more than 600%, with higher win percentage and lower VaR and drawdown, as shown in tables 3.1 and 3.2. The high profit observed in December of 2014 came from eight trades in the British Pound - Japanese Yen spreads. The results observed in this category are all from spread trades, which prove to be promising.

**Table 3.1:** results of the SeasonAlgo algorithm (source: [www.seasonalgo.com](http://www.seasonalgo.com))

Currency - Seasonal					
Resultado	Avg	#	Win #	win%	Avg Win
\$ 121.204,04	\$ 1.616,05	75	53	71%	\$ 2.900,95
Avg Loss	Best	Worst	STDEV	VaR	Max DD
\$ -1.712,95	\$ 11.025,18	\$ -19.112,45	\$ 4.129,42	\$ -6.477,61	\$ 19.112,45

**Table 3.2:** Results of the buy and hold strategy (source: [www.quandl.com](http://www.quandl.com)).

Currency - Buy and Hold					
Resultado	Avg	#	Win #	win%	Avg Win
\$ 19.077,50	\$ 149,04	128	64	50,0%	\$ 10.210,21
Avg Loss	Best	Worst	STDEV	VaR	Max DD
\$ -9.912,13	\$ 38.590,00	\$ -40.351,25	\$ 13.075,11	\$ -25.478,18	\$ 107.071,25



**Figure 5:** capital evolution chart for SeasonAlgo strategy in currency category



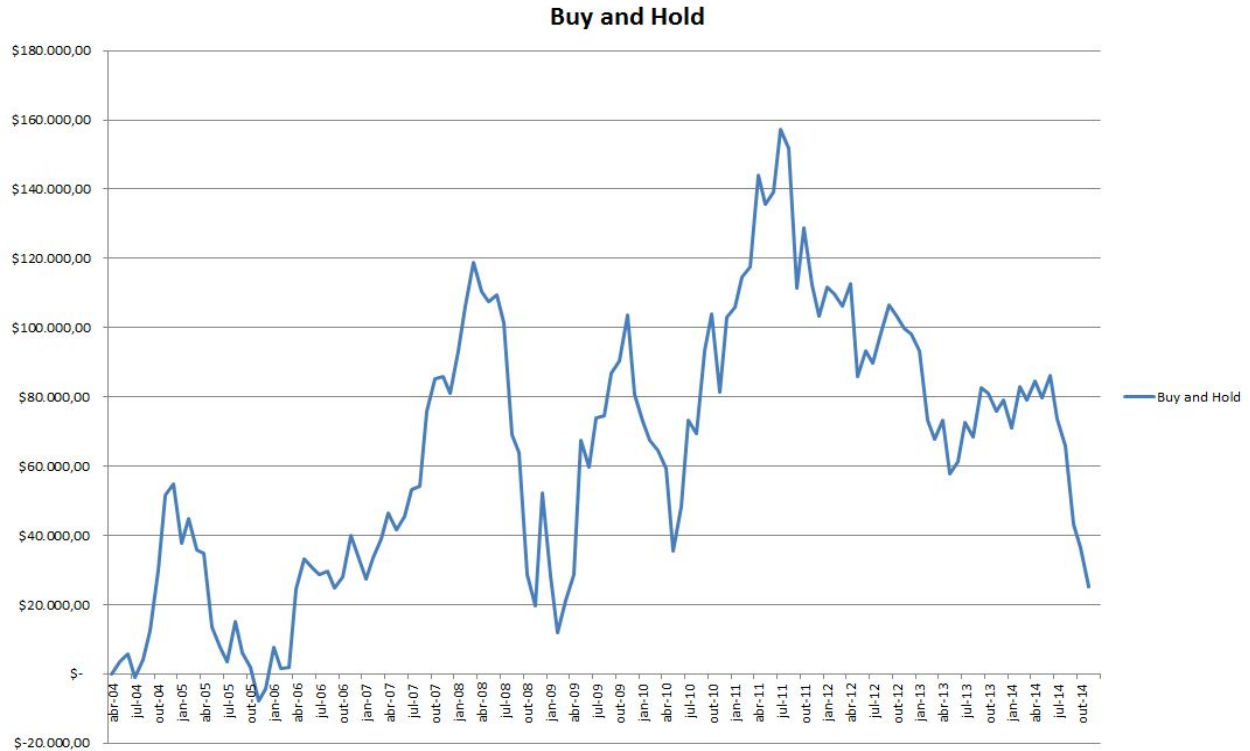


Figure 6: capital evolution chart for buy and hold strategy in currency category

### Grain-Meat

The algorithm suggested 11.852 trades between 01/12/1995 and 05/30/2015, in contracts of Feeder Cattle, Live Cattle, Corn, Lean Hogs, Wheat, Canola, Soybean, Soybean Oil, Soybean Meal. As benchmark the sum of the combined daily returns of the nine contracts were used. This particular category represents 74,5% of all the trades suggested by the SeasonAlgo algorithm. The results were proved to be promising as observed by comparing the data shown in tables 4.1 and 4.2. While having a lower VaR, the SeasonAlgo suggested trades achieved 12 times more profit than the passive trading and a win rate of 67%. Of the seasonal strategy trades, only 2% were outright positions, that can explain the low VaR of the strategy.

Table 4.1: results of the SeasonAlgo algorithm (source: [www.seasonalgo.com](http://www.seasonalgo.com)).

Grain/Meat - Seasonal					
Resultado	Avg	#	Win #	win%	Avg Win
\$ 2.460.461,12	\$ 207,60	11852	7958	67%	\$ 569,49
Avg Loss	Best	Worst	STDEV	VaR	Max DD
\$ -621,15	\$19.575,05	\$-16.000,00	\$ 1.208,55	\$-2.161,15	\$296.900,64

Table 4.2: results of the buy and hold strategy (source: [www.quandl.com](http://www.quandl.com)).

Grain/Meat - Buy and Hold					
Resultado	Avg	#	Win #	win%	Avg Win
\$ 198.916,00	\$ 38,71	5139	2662	52%	\$ 2.172,33
Avg Loss	Best	Worst	STDEV	VaR	Max DD
\$ -2.254,27	\$33.509,00	\$-27.300,50	\$3.297,02	\$-6.423,46	\$270.076,50

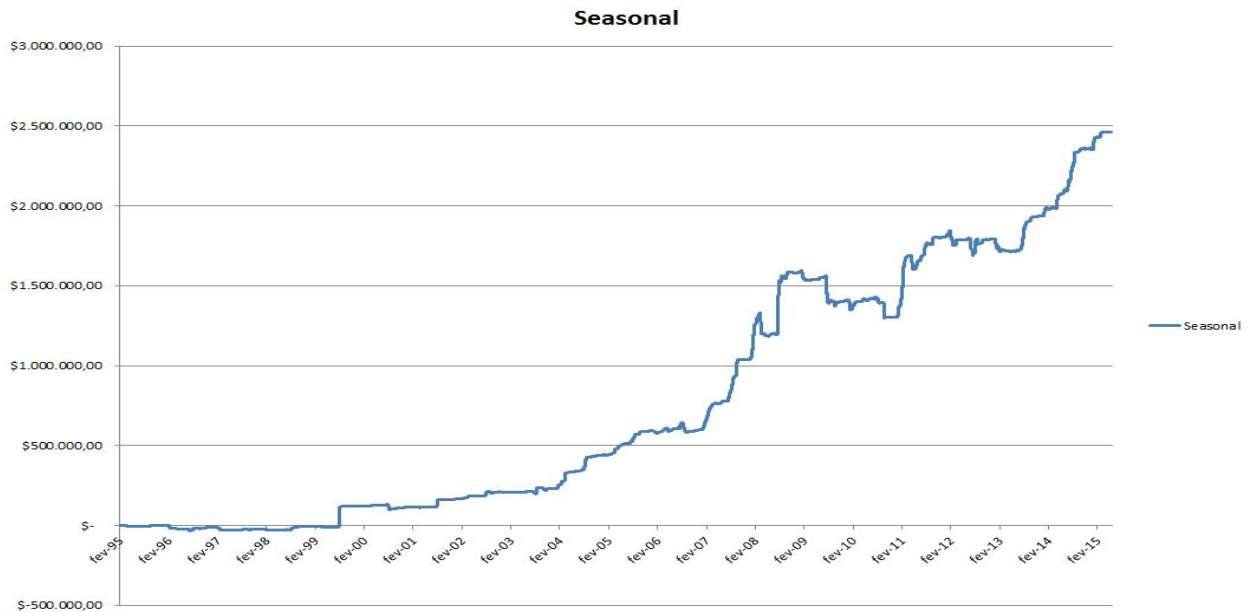


Figure 7: capital evolution chart for SeasonAlgo strategy in grain/meat category

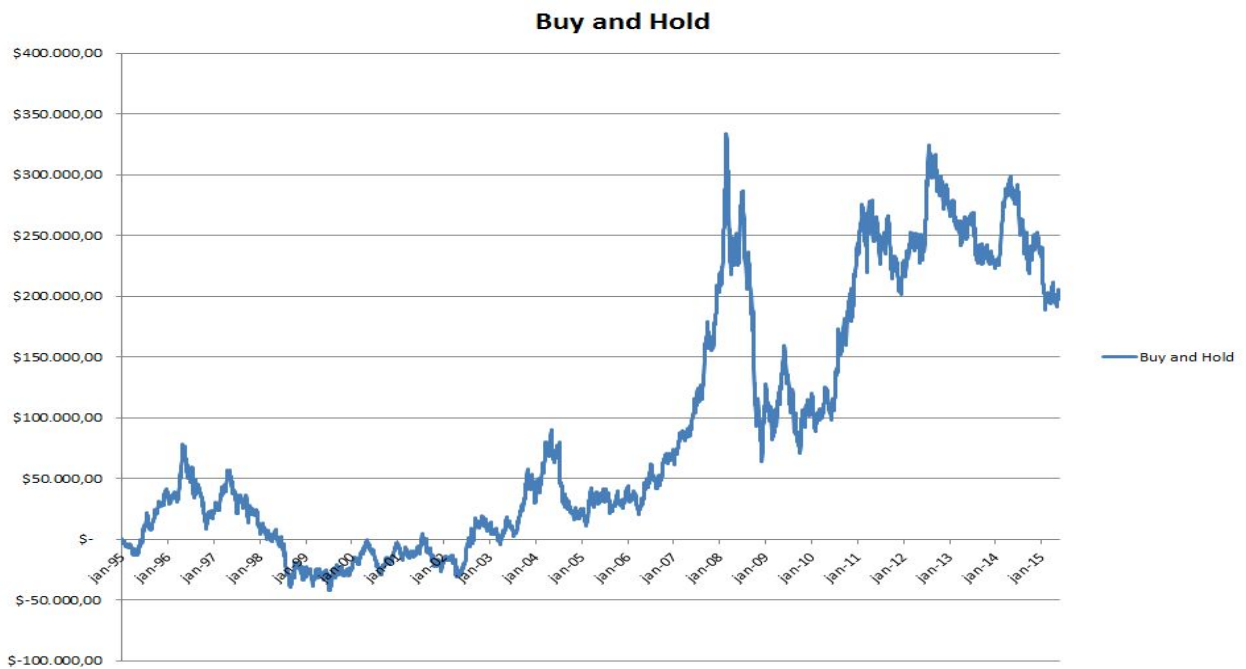


Figure 8: capital evolution chart for buy and hold strategy in grain/meat category

## Index

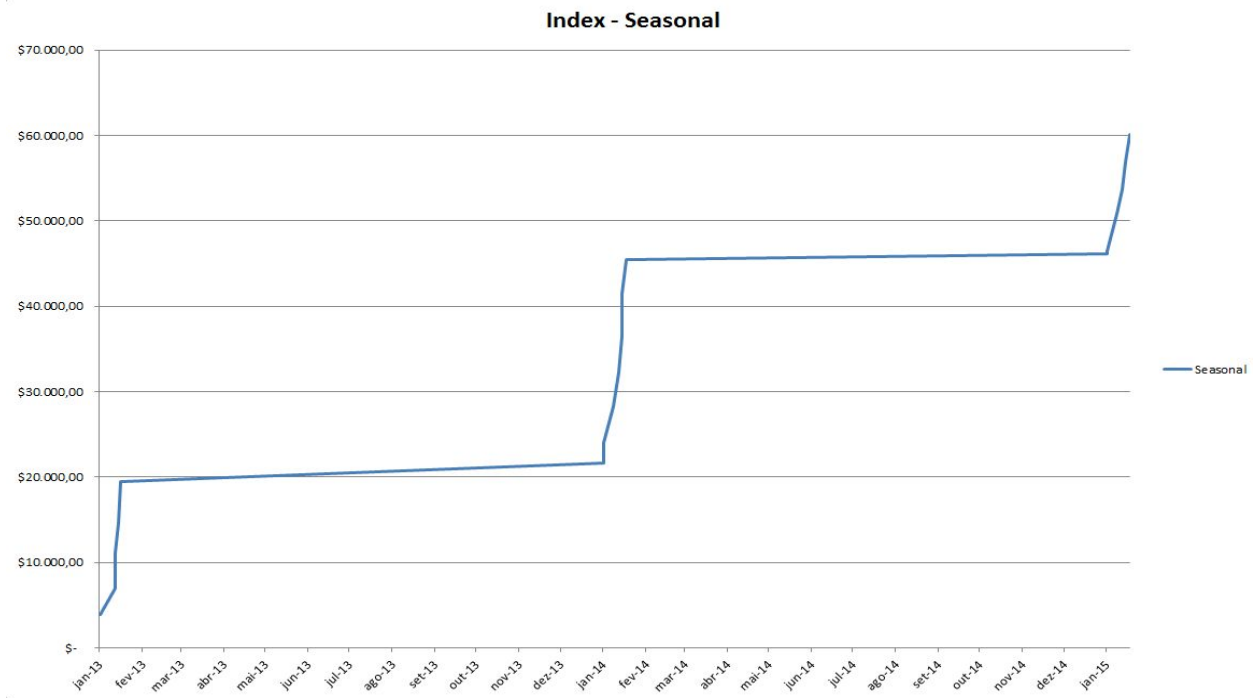
The SeasonAlgo algorithm suggested 18 trades between 11/19/2012 and 01/19/2015, in contracts of E-Mini S&P. Since all the trades occurred between October and January, without having any trade in other months, the only benchmark that could be used for this study were the monthly returns of the contract. The strategy presented no losses in the time frame presented, and consists all of outright March E-mini S&P contracts.

**Table 5.1:** results of the SeasonAlgo strategy (source: [www.seasonalgo.com](http://www.seasonalgo.com)).

Index - Seasonal						
Resultado	Avg	#	Win #	win%	Avg Win	
\$ 60.099,59	\$ 3.338,87	18	18	100%	\$ 3.338,87	
Avg Loss	Best	Worst	STDEV	VaR	Max DD	
#DIV/0!	\$ 4.874,95	\$ 312,43	\$ 1.311,33	\$ 768,67	\$ -	

**Table 5.2:** results of the buy and hold strategy (source: [www.quandl.com](http://www.quandl.com)).

Index - Buy and Hold						
Resultado	Avg	#	Win #	win%	Avg Win	
\$ 34.025,00	\$ 945,14	36	26	72%	\$ 2.107,69	
Avg Loss	Best	Worst	STDEV	VaR	Max DD	
\$ -2.077,50	\$ 4.062,50	\$ -4.412,50	\$ 2.222,23	\$ -3.410,44	\$ 4.900,00	



**Figure 9:** capital evolution chart for SeasonAlgo strategy in Index category

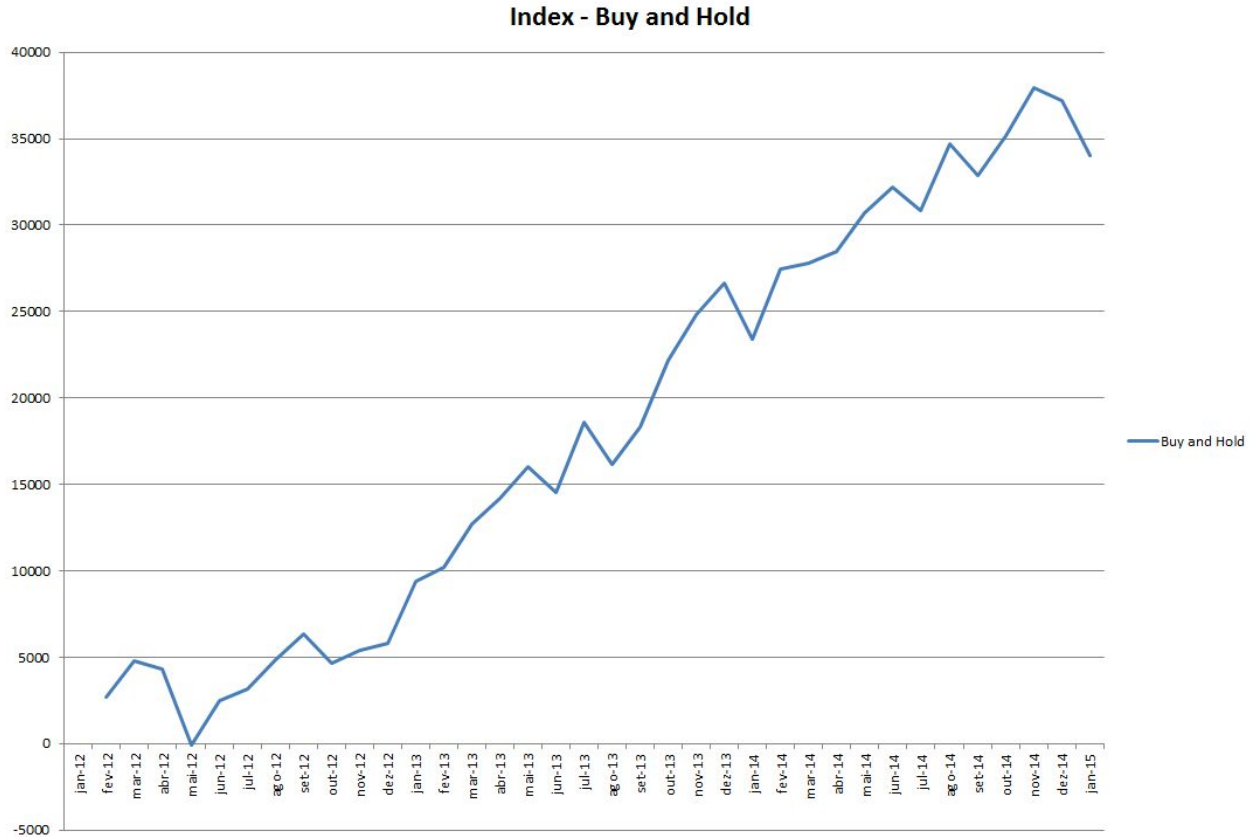


Figure 10: capital evolution chart for buy and hold strategy in Index category

### Interest Rates

The algorithm suggested 304 trades between 11/07/2009 and 11/28/2014, in contracts of 30 years T-bonds, 10 years T-bonds and EURODOLLARS. For benchmark the combined weekly returns of the three contracts were used. The strategy beat the market by more than 680%, with an impressive win percentage and lower VaR, average loss and drawdown, as shown in tables 6.1 and 6.2. We can observe a growth in the accumulated capital chart in the september to november 2011 (figure 11), that's attributed to profitable trades suggested in the 30year T-Bonds outright contracts.

Table 6.1: results of the SeasonAlgo strategy (source: [www.seasonalgo.com](http://www.seasonalgo.com)).

Interest Rates - Seasonal					
Resultado	Avg	#	Win #	win%	Avg Win
\$ 227.247,62	\$ 747,53	304	232	76,3%	\$ 1.134,56
Avg Loss	Best	Worst	STDEV	VaR	MAX DD
\$ -580,15	\$21.187,78	\$-4.718,79	\$ 2.877,83	\$-4.893,03	\$13.218,71

Table 6.2: results of the buy and hold strategy (source: [www.quandl.com](http://www.quandl.com)).

Interest Rates - Buy and Hold					
Resultado	Avg	#	Win #	win%	Avg Win
\$ 33.442,88	\$ 127,16	263	151	57,41%	\$ 2.001,26
Avg Loss	Best	Worst	STDEV	VaR	Max DD
\$ -2.399,53	\$ 7.348,62	\$ -10.775,63	\$ 2.740,01	\$ -5.243,25	\$ 36.462,12

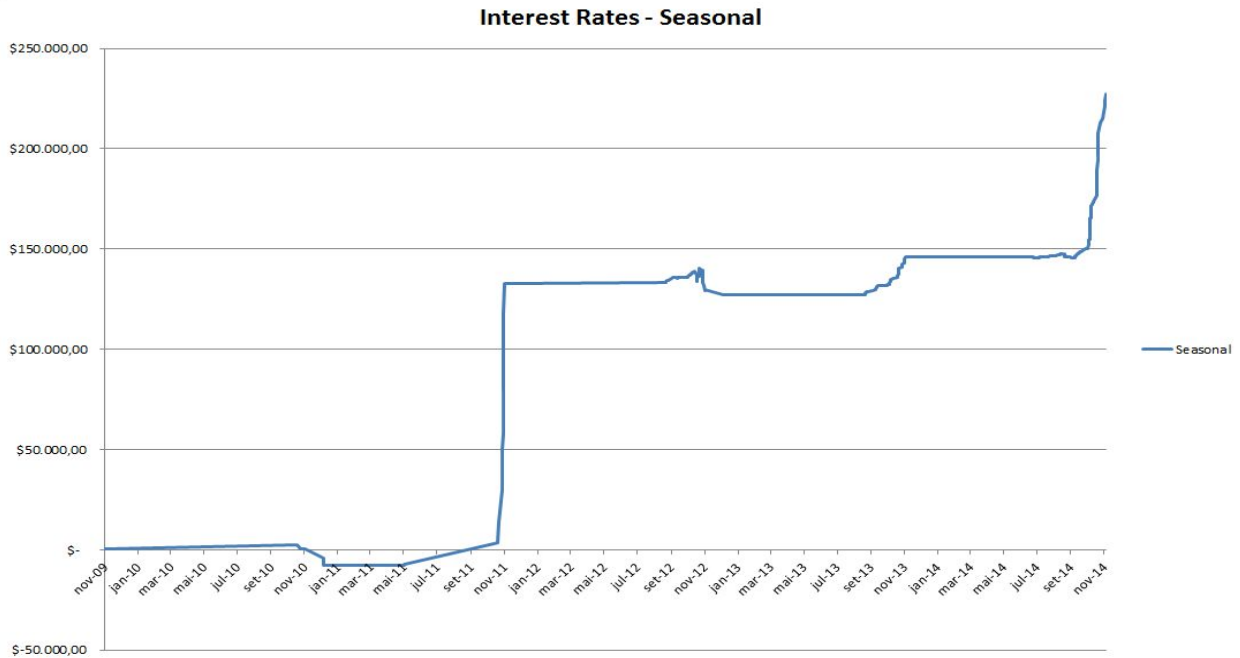


Figure 11: capital evolution chart for SeasonAlgo strategy in interest rates category

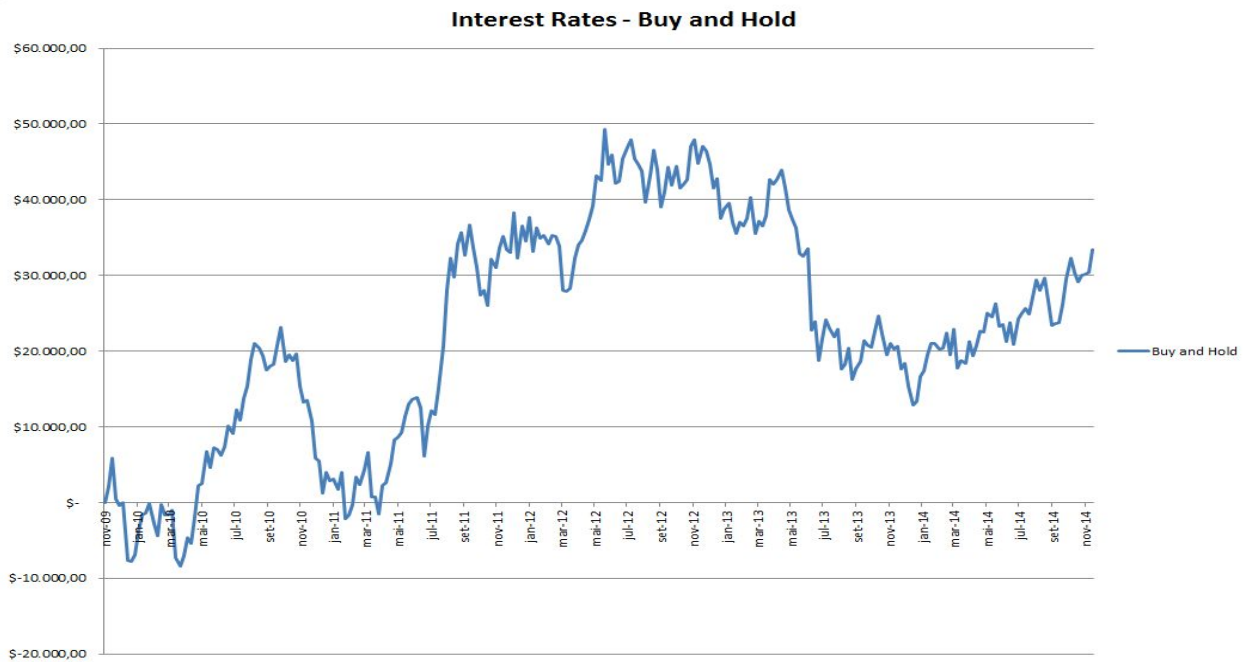


Figure 12: capital evolution chart for buy and hold strategy in interest rates category



## Metals

The algorithm suggested 1093 trades between 06/09/1995 and 03/31/2015, in contracts of Silver, Gold, Platinum, Palladium and Copper. For benchmark the sum of the weekly returns of the five contracts were used. Even though this category represents only 7% of the trades suggested by SeasonAlgo, it amounted for 70% of the profits. By conducting further analyses, it was found that the gold - platinum and gold - silver spreads alone represented 99% of the profits as shown in table 7.3. The seasonal strategy was able to beat the market by more than 2145% as shown in tables 7.1 and 7.2, with a higher win percentage and a lower average loss. However an alarming drawdown was observed between March 2013 and March 2015. During this period only 22% win ratio was observed as shown in table 7.4. This means that with the losses of the three years presented, these trades will be filtered out in the next year's suggestions made by the algorithm.

**Table 7.1:** results of the SeasonAlgo strategy (source: [www.seasonalgo.com](http://www.seasonalgo.com)).

Metals - Seasonal					
Resultado	Avg	Trades#	Win #	win%	Avg Win
\$5.887.544,09	\$5.386,59	1093	736	67%	\$10.153,62
Avg Loss	Best	Worst	STDEV	VaR	Max DD
-\$4.649,62	\$56.200,15	-\$23.299,96	\$12.601,29	-\$19.311,93	\$1.206.369,39

**Table 7.2:** results of the buy and hold strategy (source: [www.quandl.com](http://www.quandl.com)).

Metals - Buy and Hold					
Resultado	Avg	Trades#	Win #	win%	Avg Win
\$274.410,00	\$259,86	1056	582	55%	\$5.631,18
Avg Loss	Best	Worst	STDEV	VaR	Max DD
-\$6.335,31	\$55.715,00	-\$106.410,00	\$9.859,84	-\$19.065,44	\$283.312,50

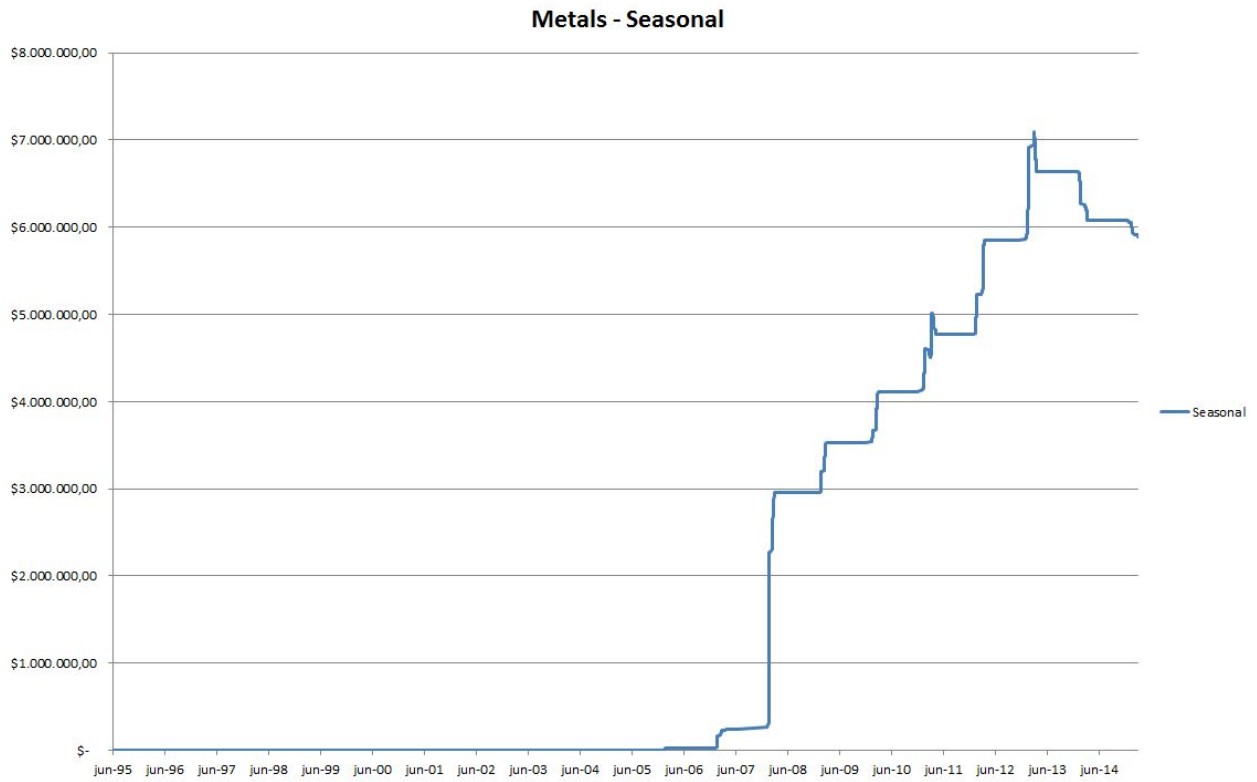
**Table 7.3:** results of the gold - silver and gold - platinum spread trades in SeasonAlgo Strategy (source: [www.seasonalgo.com](http://www.seasonalgo.com)).

Gold - Platinum and Gold - Silver Spreads Results					
Resultado	Avg	#	Win #	win%	Avg Win
\$ 5.856.709,35	\$ 7.506,20	780	542	69%	\$ 13.569,31
Avg Loss	Best	Worst	STDEV	VaR	Max DD
\$ -6.301,38	\$56.200,15	-\$23.299,96	\$14.338,30	-\$20.596,86	\$1.154.699,24

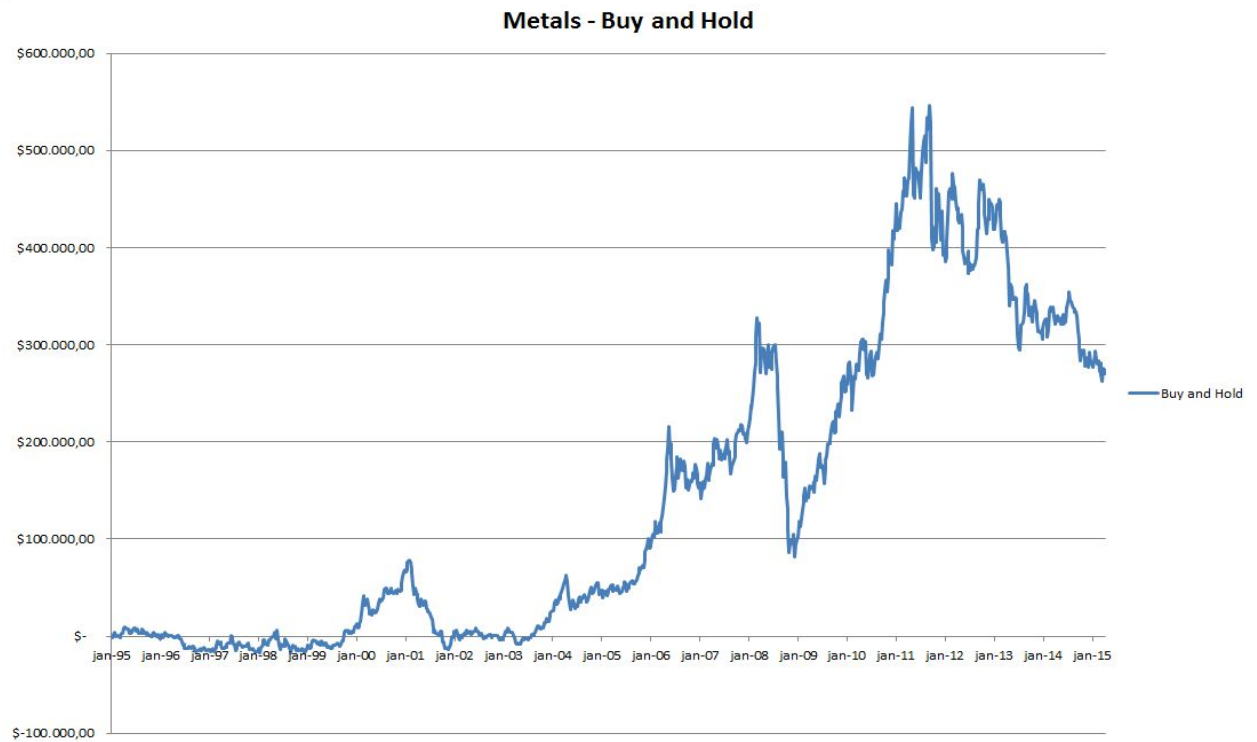
**Table 7.4:** results of the SeasonAlgo strategy between march 2013 and march 2015 (source: [www.seasonalgo.com](http://www.seasonalgo.com)).

Metals - March 2013 to March 2015					
Resultado	Avg	#	Win #	win%	Avg Win
\$ -1.203.559,44	\$ -4.011,86	300	66	22%	\$ 152,95
Avg Loss	Best	Worst	STDEV	VaR	Max DD
\$ -5.253,91	\$ 3.909,85	-\$12.869,92	\$ 3.646,75	-\$11.159,50	\$1.206.369,39

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**Figure 13:** capital evolution chart for SeasonAlgo strategy in Metals category



**Figure 14:** capital evolution chart for buy and hold strategy in Metals category



## Foods

The SeasonAlgo algorithm suggested 2155 trades between 12/01/1996 and 02/18/2015, in contracts of Cocoa, Cotton, Coffee, Lumber, Orange Juice, Robusta Coffee and Sugar. For benchmark the sum of the weekly returns of the seven contracts were used. Despite the lower VaR, average loss and higher win percentage, the results for this specific category were not promising due to the high drawdown and loss as presented in tables 8.1 and 8.2. A large downfall was observed in 2010 of the accumulated capital chart as shown in figure 15. This was caused by losses in outright coffee positions. The outright suggested positions and the spread trades were separated as shown in tables 8.3 and 8.4, in order to see that the spreads-only positions were able to beat the buy and hold strategy with lower VaR and Drawdown.

**Table 8.1:** results of the SeasonAlgo strategy (source: [www.seasonalgo.com](http://www.seasonalgo.com)).

Foods - Seasonal					
Resultado	Avg	#	Win #	win%	Avg Win
\$ -129.622,37	\$ -60,15	2155	1140	52,90%	\$ 726,04
Avg Loss	Best	Worst	STDEV	VaR	Max DD
\$ -1.007,69	\$ 10.526,92	\$ -13.481,30	\$ 1.992,72	\$ -3.965,88	\$ 585.793,70

**Table 8.2:** results of the buy and hold strategy (source: [www.quandl.com](http://www.quandl.com)).

Foods - Buy and Hold					
Resultado	Avg	#	Win #	win%	Avg Win
\$ 33.366,55	\$ 35,12	950	492	51,79%	\$ 3.556,80
Avg Loss	Best	Worst	STDEV	VaR	Max DD
\$ -3.747,99	\$ 20.166,90	\$ -23.669,85	\$ 5.025,32	\$ -9.814,51	\$ 167.306,00

**Table 8.3:** results of the SeasonAlgo strategy on outright only positions (source: [www.seasonalgo.com](http://www.seasonalgo.com)).

Foods - Seasonal -Outright Positions					
Resultado	Avg	#	Win #	win%	Avg Win
\$ -227.999,95	\$ -603,17	378	194	51,32%	\$ 2.650,79
Avg Loss	Best	Worst	STDEV	VaR	Max DD
\$ -4.056,03	\$ 10.526,92	\$ -13.481,30	\$ 4.552,30	\$ -9.525,69	\$ 591.682,54

**Figure 8.4:** results of the SeasonAlgo strategy on spread only positions (source: [www.seasonalgo.com](http://www.seasonalgo.com)).

Foods - Seasonal - Spread Positions					
Resultado	Avg	#	Win #	win%	Avg Win
\$ 98.377,59	\$ 55,36	1777	946	53,24%	\$ 331,32
Avg Loss	Best	Worst	STDEV	VaR	Max DD
\$ -280,38	\$ 5.039,99	\$ -2.650,01	\$ 575,59	\$ -1.072,80	\$ 73.004,56

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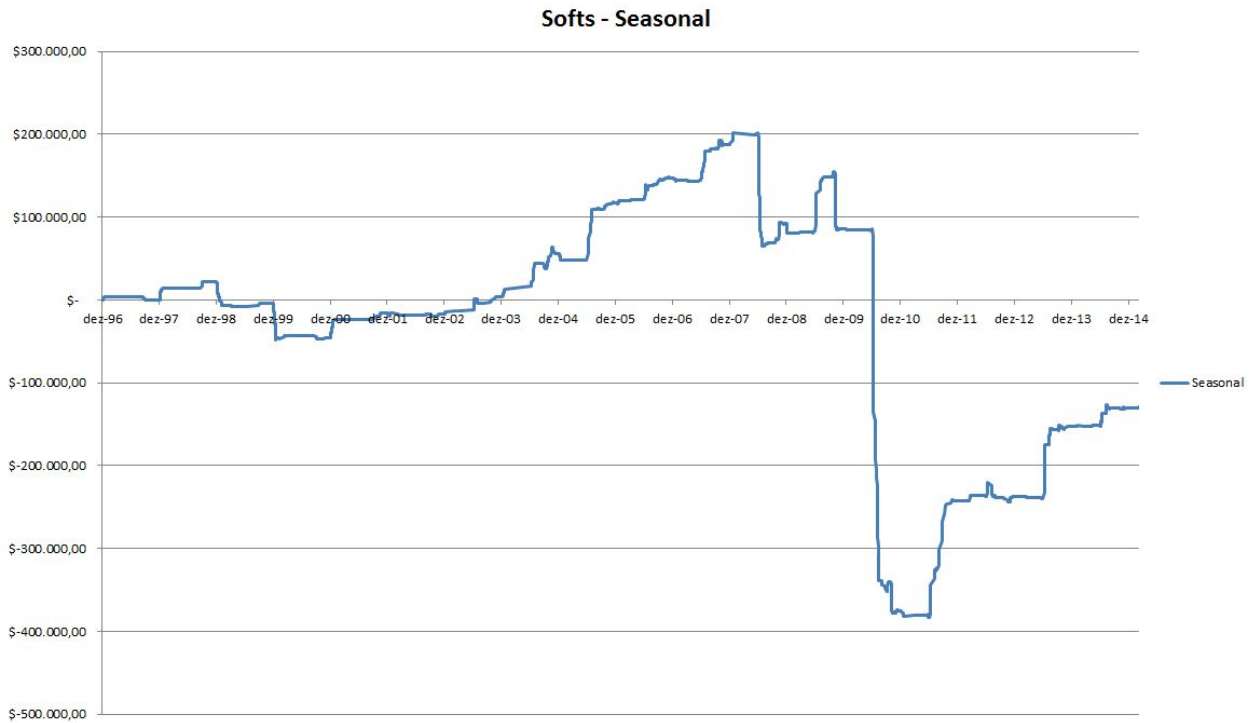


Figure 15: capital evolution chart for SeasonAlgo strategy in Foods category

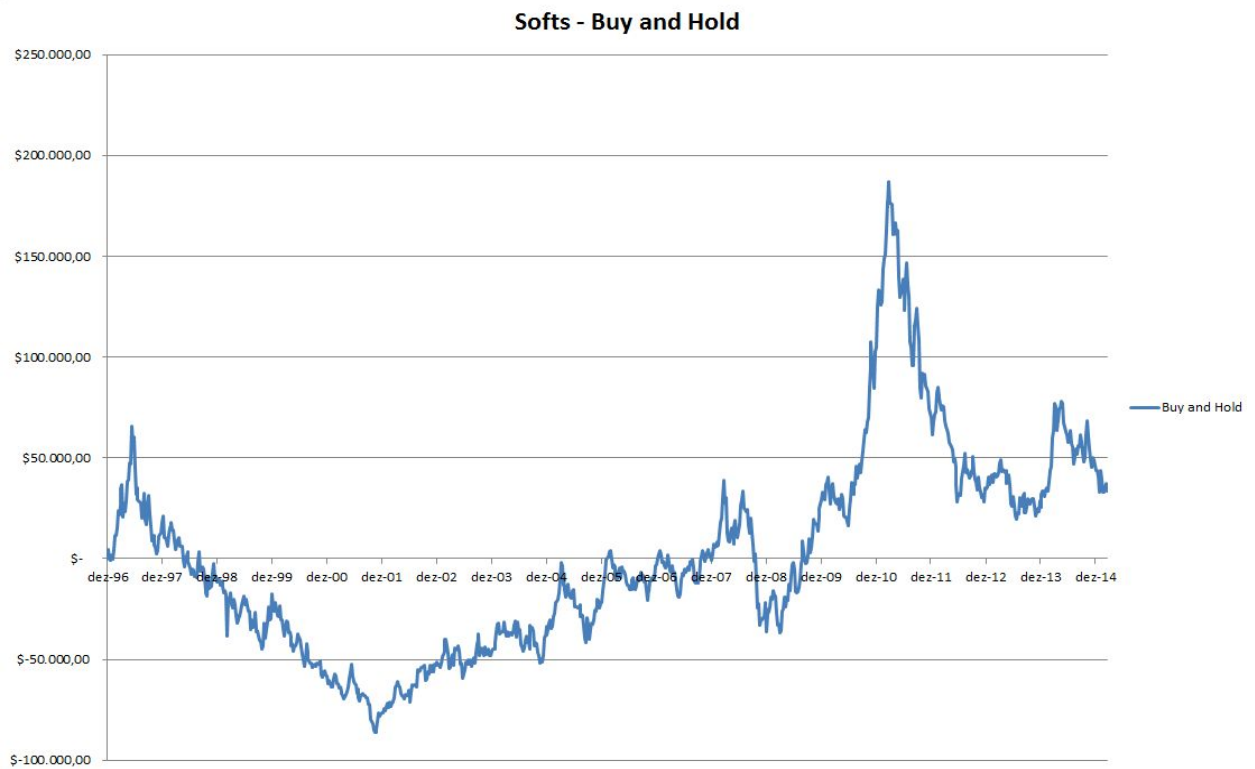


Figure 16: capital evolution chart for buy and hold strategy in Foods category

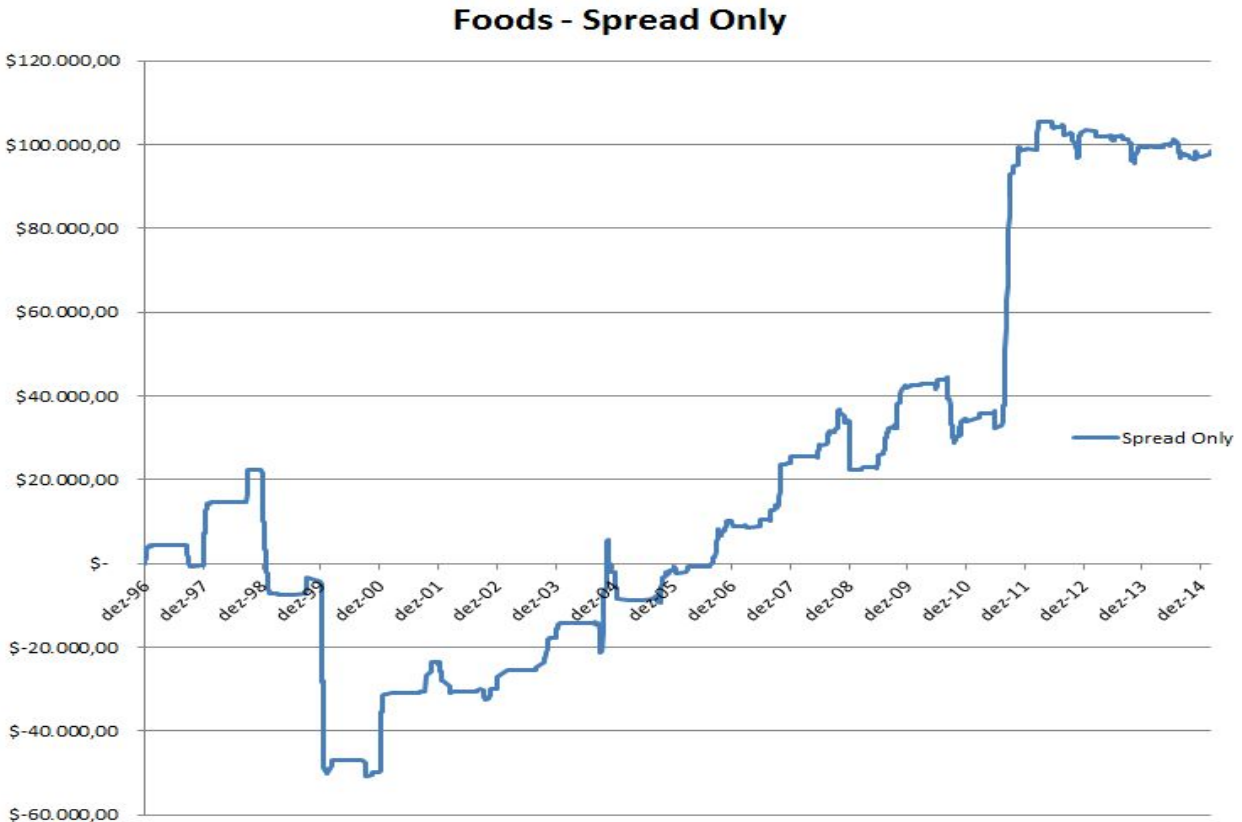


Figure 17: capital evolution chart for SeasonAlgo strategy in Foods category - Spread positions only

## Conclusion

The aim of the study was to determine whether the proposed algorithm is able to identify and exploit seasonalities in commodities markets profitably. The obtained results showed that the strategy was able to beat the markets in 5 of 7 categories, while in all categories the win ratio was higher and VaR was lower. As shown above, the reduction of the risk of the strategy relies on the wide use of spread positions. While the results cannot be used as proof of seasonality in commodities markets, the strategy consistently beat the markets by a large margin, especially at the Grain-Meat category. The results of the analysis, of course, can not serve as the sole basis for decisions on whether use the strategy not. It was not and is not the aim of the work. The conclusions should serve mainly as one more tool for better planning and more effective business decisions. The lessons learnt here can be used to improve trading systems, built on trading futures calendar spreads and seasonality. Future work can be done in this strategy, as watching how it reacts in real trading, analysing different time frames success rates, finding out if the length of the trade influences in the profitability, the distance of the legs in intracommodities markets and so on.

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## **Spreadsheets**

**All spreadsheets can be found [here](https://goo.gl/6J41R1). ([goo.gl/6J41R1](https://goo.gl/6J41R1))**