Technical Trading Systems in U.S. Commodity Futures Markets

Abstract

The purpose of this study was to assess the forecasting power of simple technical trading systems in futures markets using industry standard backtesting procedures. This study breaks down the performance of several technical trading systems optimized over a ten-year period in corn, soybeans, and Chicago wheat. We use Tradestation's backtesting program to evaluation the trading systems according to various metrics, such as profitability, risk/reward ratios, and measures comparing performance to transaction costs were also included. Our study removes the unrealizable roll yield by backtesting on back-adjusted data provided by Tradestation. The systems generated results that were above transaction costs; however, excess returns over the returns of holding Treasury notes were not overly appealing. Additionally, returns throughout the period were not consistent; there were periods of higher returns and periods of lower returns that were less variable. Nonetheless, the returns of the three grain contracts were fairly consistent across all systems, a point that could be valuable when analyzing factors such as portfolio diversification and risk management. The system results presented here are best case scenarios because they present results of optimizing parameters of the trading systems. Real-time results would show a performance decay. Future research could optimize and back test using a walk-forward approach to limit over fitting biases. The intent of this paper is to lay a framework for further tests and applications of the value in evaluating the performance of popular technical indicator systems that are so prevalent in today's markets.

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Introduction

Efficient markets should not permit any one trading strategy to make consistent profits. Though there is evidence of relative efficiency of futures markets (Kuruppuarachchi et al. 2019, McKenzie and Holt 2010, and McKenzie et al. 2002), other evidence suggests profitable strategies can exist for a period of time before conditions change or profits get competed away (Chordia and Shivakumar 2002). An important issue in evaluating trading systems in commodity futures markets is to properly dispose of the 'roll yield' (the difference between the price of an expiring contract and the next to expire contract) which is not a tradable return.

Our paper examines whether excess returns existed in U.S. grain futures markets from trading common technical systems. We employ systems that encompass three styles of markets, trending, breakout, and mean reversion to see if different styles of system are better suited in different market regimes.

Our paper is an update and a complement to the findings in (Lukac et al. 1988), which found mixed results in profitability of trading systems considered. Shang et al (2022) found that a momentum strategy did not beat a benchmark portfolio in twenty-two futures markets. Shang's result contradict Moskowitz et al.'s (2012) finding that momentum in grain markets could be predicted by the slope of the forward curve. When they account for the roll yield Shang et al find that little momentum returns are present.

Our paper contributes to this literature by testing the performance of several classic trending, breakout, and mean reversion trading systems using back adjusted data that eliminates the unattainable roll yield that can cloud futures trading system results. Our three main findings are: 1) The trading systems achieved periods of good returns, even after eliminating the roll yield. 2) Periods of profitability correspond to times of heightened volatility in U.S. grain markets, regardless of strategy style. 3) Nevertheless, the 10 year average returns were not much greater than holding Treasury bills.

Methods

To perform the tests, a combination of eight technical trading systems were selected. Four of the strategies were various trend-following systems, two were channel systems, and two were momentum oscillators. Each system could generate long and short orders and results showed that each system was in the market nearly 100% of the timeframe tested[1].

Trend-following systems

Single Moving Average (SMA): The system uses closing prices to calculate a simple moving average using closing prices for each trading period. The system is always in the market, either long or short, and uses a filter of number of days required to confirm the signal before an order is triggered.

Moving Average 2 Line Cross (DMA): This system uses closing prices to calculate two simple moving averages, a longer and shorter term, and is always in the market. A long (short) entry is triggered when the shorter moving average crosses above (below) the longer moving average, on the first bar after the signal occurs.

[1] Each system was in the market at least 99% of the timeframe tested; the reason for this is start date of the initial first trade may not have been on the first date selected but once entry was triggered, the systems never left the market.

Pivot Reversal Strategy (PR): This system triggers a long entry on the breakout of a pivot high point and short entry is triggered on the breakout of a pivot low point. These points are calculated using a set number of bars which are defined in the strategy parameters.

Moving Average Convergence Divergence (MACD): This system uses three exponential moving averages to determine order entry. A fast exponential average and slow exponential average are used to calculate a value for the MACD. A third exponential average is calculated to represent the MACD. Long (short) entry occurs when the MACD crosses above (below) the zero value, on the next bar at open. This system is always in the market.

Channel Breakout Systems

The Price Channel (PC)**:** uses a price band calculated based on a set number of bars and signals are calculated using the closing price of each period. The system is a breakout system and buy stop orders are triggered when prices close above the upper band and entry levels are placed at the highest high over a number of bars[2]. Opposingly, sell stop orders are triggered when the price closes below the lower band, and are placed at the lowest low of bars used in the calculation. The system is always in the market.

Keltner Channel strategy (KC): Upper and lower deviations are calculated and represented as channels. Long orders are triggered upon a price breakout over the upper channel; conversely, short orders are triggered upon the crossing of prices below the lower channel. For long (short) signals, buy (sell) stops are placed at the high of the bar which defined the breakout, plus 1 point.

[2] This number of bars is used to calculate the length of time the indicator is measured over, similar idea as the length of a moving average.

Momentum Oscillator or Mean Reverting Systems

Bollinger Band Strategy (BB): This strategy uses a range of ‘normal’ prices defined by two bands, an upper and lower band, calculated as 2 standard deviations from a simple moving average. As prices cross below the lower band, a buy stop order is triggered for the next bar where the low has crossed back above the lower band. The stop is places at the level of the lower band. Short entry is calculated in the same manner, but opposingly; as prices cross the upper band, a sell stop is placed at the level of the upper band on the next bar in which the bar high crosses below the upper band. The idea of this reversion strategy is to buy (sell) when prices are low (high) compared to ‘normal’ prices, based on a simple moving average calculation.

The Relative Strength Index strategy (RSI)**:** uses an index to calculate the strength of prices and “speed” of the market. This strategy issues a long entry when prices cross above oversold levels and triggers a short entry when prices cross below overbought levels. Inputs for the overbought/oversold levels were left at standard settings of 30 for oversold and 70 for overbought, for the backtesting.

Commission, Slippage, and Other Assumptions

For each system used, commissions and slippage were set at $50 per round turn and fees at $5 per round turn. This was done to adjust for transaction costs, as the forecasting power of trading systems is first tested by evaluating performance with transaction costs factored in. This reduced inaccuracy of results due to trading volume, whether high or low.

It is also worth noting how each system was optimized for the entire 10-year period to be adjusted from standard system input settings. While walk-forward analysis would be preferred in most standard backtests, choosing to optimize for the entire 10-year period was the approach used with the aim of identifying changing market trends (up, down, sideways). The downfall to this is that the optimized systems did not see any new data and the weight of the results rests on this fact. However, the simple fact that the results generated are based on the most profitable combination of inputs, for that period and system, does offer a valuable perspective when analyzing only one sector, independent of a more portfolio-based approach of a multitude of markets.

Backtesting technical trading systems in futures markets is difficult because the life of a futures contract is limited. The tests were conducted in the nearest contract to expiration and were subsequently rolled to the next contract when the level of open interest in the nearest deferred contract exceeded that of the nearest to expiration. This is the industry standard of adjusting continuous contracts. Since most trading occurs in the nearby contract month, the trading took place with these settings to fit the nature of the systems more accurately.

Performance Assessment

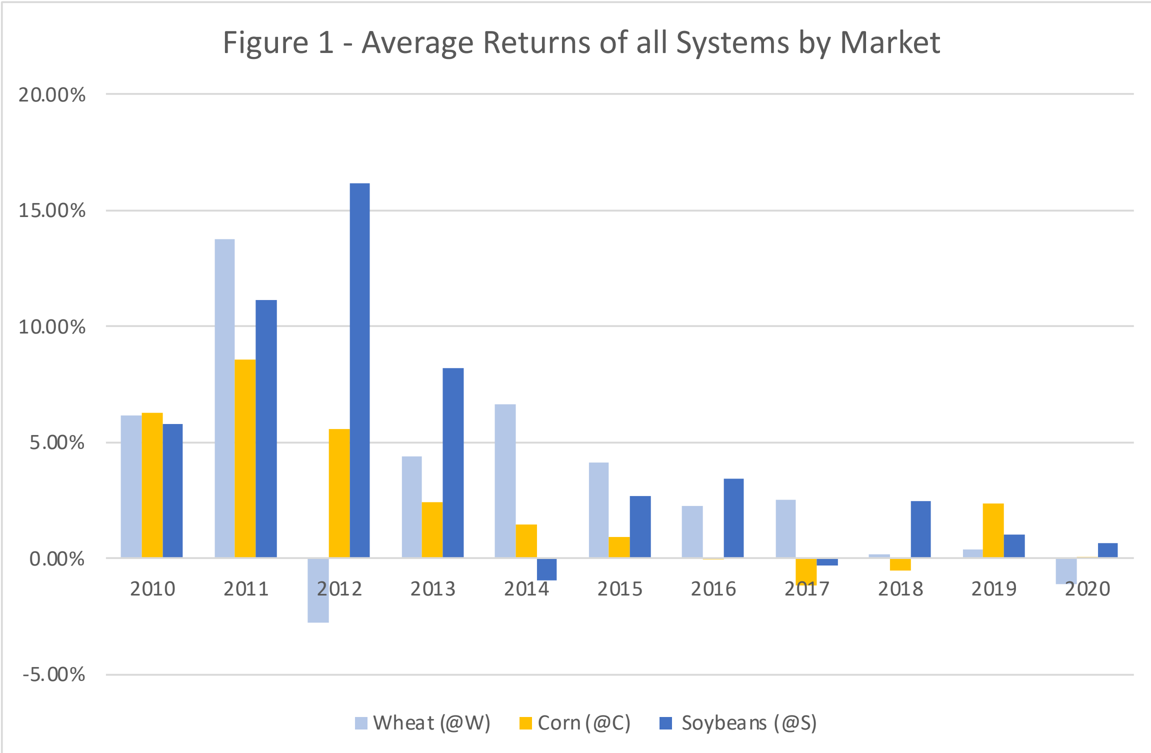
Results for each system and market were analyzed using the performance summary reports generated by Tradestation’s backtesting applications. Returns for the systems were calculated based on the returns on initial capital, which was $100,000. Buy and hold returns are included to compare performance results. The tests were conducted using daily price bars to represent price data on the Tradestation platform for standard instrument backtesting. All data was collected from the strategy performance reports generated by Tradestation. To adjust for futures roll periods, standard settings set by Tradestation were assumed, that all trades would occur during the front, most liquid month and open positions would subsequently "roll" to the next deferred month when the open interest of the second nearby contract exceeded that of the first, nearest to expiration contract, prior to first notice day. Tradestation then subsequently add or subtracts a constant to all data that exists before the rollover point, all the way back to the beginning of the data series (Tradestation).

Data

Only three markets were tested to limit the scope of these systems to a specific sector: the grains. The period of our study was 2010-2020, including the years of 2012 and 2013 when large profits in the grain sectors could have been achieved during the price trends caused by historically tight grain supplies in 2012 and 2013. The bars followed the generic open, high, low, close format and inputs for system calculations were based on the closing price for each period. Following the early years in the period tested, the price action of these markets changed drastically from huge trends and swings to more range-bound, sideways action. The variation in this action harnessed an environment worthy of testing the performance of these indicator systems and the similarity between the contracts in the grains sector helped maintain congruency in evaluating the performance of an individual sector alone. The results of this test should not, therefore, necessarily be congruent or true for performances across other contracts. For instance, having a portfolio of just grain futures alone seems arbitrary and likely not attractive to many investors of technical trading systems. However, being able to look at various industries independently to evaluate system performances can be beneficial and was the intent of this test.

Results

For the entire 10-year period tested, the returns generated by the systems were profitable above the associated transaction costs, indicating that disequilibrium is present which the systems detected. The results were pulled from the strategy performance reports generated by the Tradestation platform's generic backtesting programs. To evaluate the returns by market, we used the compounded annual returns on capital for each system within a market and calculated the average for all systems traded on that market. This calculation was done for every year across the three markets, corn, soybeans, and wheat. The average returns of all systems within each market is depicted in Figure 1 (below). While this illustration alone is not overly useful, it does provide a helpful look into how the systems performed within each market over the entire time period. It would be logical to assume that traders employ more than one indicator in strategy, often combinations of many indicators or systems. This assumption does not affect the overall results of this paper, but we found this chart helpful in framing the bigger picture at what we're after. Results were fairly congruent across the three grain markets, as shown in Figure 1. Data like this could prove to be a helpful point in portfolio construction and diversification, as employing more than one single indicator or system is diversification of strategy but is not the intent of this paper. Average returns of each individual system across all three markets, within each year, are summarized in Table 1. This gives a deeper look into the average returns of the 8 systems, plotted to compare results by market in a different view. It becomes evident that differences exist among the returns of each individual system, within each year. This table was more helpful because the congruency of performance that existed between the three markets, corn, soybeans, and wheat.



Notes: Average returns across all systems by market. Returns from backtesting on back-adjusted data from corn, soybeans, and Chicago wheat CBOT futures contracts from 2010-2020.

Table 1: Annual Results of Each Trading System Averaged Across Results in Corn, Soybeans, and Chicago Wheat Markets, 2010-2020

System	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Average
SMA	8.60%	10.07%	-2.64%	1.72%	-1.38%	1.41%	1.82%	-4.08%	-0.80%	-0.01%	4.41%	1.74%
DMA	13.15%	6.56%	11.93%	6.12%	8.65%	3.13%	2.05%	0.17%	0.34%	3.79%	1.12%	5.18%
PR	-1.34%	-0.11%	10.48%	4.57%	0.81%	4.54%	2.13%	1.70%	1.88%	3.66%	2.22%	2.78%
MACD	6.79%	14.70%	9.89%	8.45%	4.29%	1.80%	-0.36%	-0.20%	2.66%	-1.24%	0.23%	4.27%
PC	3.66%	10.75%	8.04%	-0.06%	7.90%	-0.66%	0.76%	-0.23%	-0.15%	1.42%	2.00%	3.04%
KC	11.85%	-2.88%	11.01%	5.30%	9.15%	-1.32%	3.30%	0.75%	-0.57%	1.41%	4.12%	3.83%
BB	6.81%	26.26%	-0.93%	5.67%	-4.67%	7.21%	4.92%	2.17%	-1.33%	-0.13%	-8.05%	3.45%
RSI	-0.72%	23.90%	2.95%	8.22%	-5.56%	4.54%	0.65%	2.73%	3.70%	1.20%	-6.99%	3.15%
Average	**6.10%**	**11.16%**	**6.34%**	**5.00%**	**2.40%**	**2.58%**	**1.91%**	**0.37%**	**0.72%**	**1.26%**	**-0.12%**	**3.43%**

Notes: System abbreviations are as follows: SMA = Single Moving Average, PC = Price Channel, DMA = Dual Moving Average, KC = Keltner Channel, PR = Pivot Reversal, BB = Bollinger Bands, MACD = Moving Average Convergence Divergence, RSI = Relative Strength. Systems backtested on back-adjusted data from corn, soybeans, and Chicago wheat CBOT futures contracts from 2010-2020.

Both illustrations show that profits decreased over time. The highest returns across all systems were achieved in the first four years and subsequently declined thereafter. This is also reflected by the returns for all systems by market, shown in Figure 1. The DMA system and KC system generated the highest compounded average annual returns across the systems, with only three years[3] being below the cumulative average[4] of all systems, in that respective year.

Figure 1 helps illustrate the congruency between contracts in the grain sector. Similar trends in performance results were still evident, with wider, more varying results in the early years but declining as time went on. But the results tapered off as time progressed. To remain consistent with the framework of this paper, we did not dive deeply into comparing congruency among the three markets, which could provide room for further research. Rather, we chose to remain focused on the testing of disequilibrium among such similar markets, but it should be noted that this could be an assumption that may lead to different results being achieved. The similarities in system results between the three markets is important to note and could warrant further research.

While these profitability figures are significant above transaction costs, alone they are not useful in evaluating system adversity. Further evaluation is needed to assess profitability of technical trading systems. To further evaluate profitability, we employ a few industry standard metrics which are generated by Tradestation's performance reports in the backtesting procedure, which we discuss next.

[3] Compounded average annual returns were below average for the DMA system in years 2011, 2017 and 2018; returns were below cumulative average for the KC system in years 2011, 2015, and 2018.

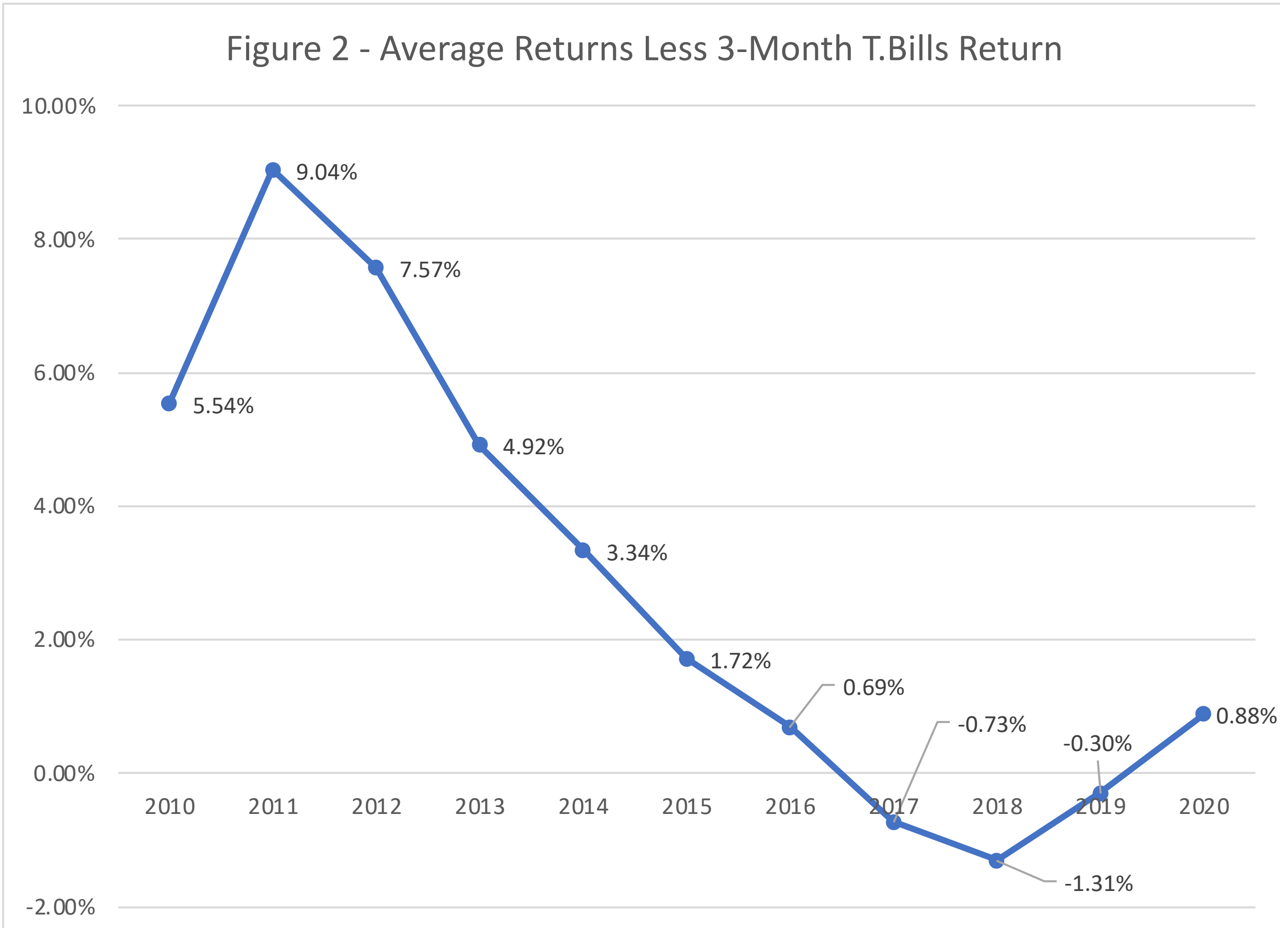
[4] Cumulative averages are simply referring to the average of the ratios of each system, used as a general benchmark to help compare system performances individually.

Assessing Returns to Risk

This study utilizes the framework provided by capital market theory to analyze the returns of the systems against returns of the 3-month treasury bills secondary market rate for the same period (St Louis Federal Reserve, 2022).The concept of capital market theory is widely utilized in the financial industry in terms of portfolio analysis and construction. The theory provides a framework for analyzing returns of a hypothetical portfolio against another asset to evaluate the returns to identify opportunity costs associated with investing capital in another venture. The 3-month treasury bills are the “risk-free” rate of the open market, as the US Federal Reserve is not likely to default on its payments of these notes and they provide a good instrument for analyzing the opportunity costs associated with the money in a portfolio used for trading. The point here is that an investor of capital in these systems could go to the market and easily achieve the returns of the 3-month treasury bills as an alternative. This study assumes this to be the opportunity costs of the capital associated with each of these systems. To evaluate the system returns compared to the cost of money, the following formula was used:

$$R_i = [R_S - R_T]$$

Where R_i represents the returns of the investment capital, i, associated with the systems. R_s is the annual returns of the systems, s. R_T represents the returns of the 3-month treasury bills as published by the St. Louis Federal Reserve (St Louis Federal Reserve, 2022). The results are graphed in Figure 2.



Notes: Excess returns over the returns from holding Treasury bills across all systems and all markets. Returns from backtesting on back-adjusted data from corn, soybeans, and Chicago wheat CBOT futures contracts from 2010-2020.

The results in Figure 2 are congruent with the data collected thus far in that returns for most years were above those associated with the risks associated, under capital market theory. While there were only three years (2017-2019) where the results were less than the returns associated with a risk-free asset, years 2016 and 2020 were additionally low at below 1%. The issue here is that there must be a significant level of return associated with the systems when comparing it to a risk-free asset. For example, an investor would likely not be attracted to switch their assets over to a portfolio driven by technical trading systems if the returns were less than 1% greater than those associated with essentially risk-free assets. There is yet another element of risk/reward to this decision in that returns to the investment tool must be significantly greater. This raises the point that further evaluation is needed. While this level may vary from investor to investor, and that is ultimately tough to quantify, there are yet some other metrics which prove helpful in evaluating the opportunity costs of technical trading systems: performance measures ratios.

Three Performance measures were used to assess the performance quality of the systems. Variance among systems was also looked at. The ratios used were the Return Retracement Ratio, the Rina Index, and the K-Ratio, all generated by Tradestation's strategy performance report[5]. The results are shown in Table 2 below:

[5] Detailed definitions for each of these ratios can be found in Appendix I

Table 2. System Performance Metrics Averaged Across

System	RRR	Rina Index	K-Ratio
SMA	0.14	-15.50	0.01
DMA	1.43	47.67	0.21
PR	0.49	23.88	0.20
MACD	1.25	41.67	0.15
PC	0.53	16.14	0.12
KC	0.79	16.47	0.13
BB	0.74	15.11	0.14
RSI	0.47	15.01	0.12
Average	**0.73**	**20.06**	**0.13**

RRR = Return Retracement Ratio

SMA = Single Moving Average PC = Price Channel

DMA = Dual Moving Average KC = Keltner Channel

PR = Pivot Reversal BB = Bollinger Bands

MACD = Moving Average Convergence Divergence RSI = Relative Strength

At first glance, there is some variation between the systems, some being above and others below the cumulative average[6]. The four trend-following systems (SMA, DMA, PR, and MACD) generated the highest ratios across the board, with the DMA leading the way with the highest ratios across all three metrics. Behind that were the two channel systems (PC and KC) and closely followed by the two momentum/oscillator systems (BB and RSI).

In general, the higher the value associated with each performance evaluation metric, the more robust the system should be. Overall, the results were not attractive. For example, industry preferences for RINA Index figures are typically a value of at least 100 or greater, 200 being preferred (Inovance). The average RINA Index for all the systems was a mere 20.06, indicating that the systems did not achieve a significant reward when compared to time in the market and the monthly drawdown associated with the system. The highest RINA Index figure was generated by the DMA system at 47.67, followed closely by the MACD. The remainder of the systems were much lower.

The RRR and the K-Ratios provide a close look at similar attributes of a system: returns over time. However, these two ratios indicate slightly different results. For example, the RRR for the DMA is almost three times that of the RRR of the PR. Meanwhile, the K-Ratio for the same two systems was 0.21 for the DMA and 0.20 for the PR. This is best explained by the inclusion of drawdown in the RRR ratio. Therefore, at first glance at the K-Ratios alone may discourage interest in these systems and markets for these timeframes, as the ratios are all fairly consistent across all systems, very low. However, the RRR shows slightly different results, identifying

[6] Cumulative averages are simply referring to the average of the ratios of each system, used as a general benchmark to help compare system performances individually.

greater differences between systems. This is important to note because of the differences in the nature of the systems- trend-following, channel, and momentum/oscillator. The congruency between the tested markets (Figure 1) helps support the accuracy of the figures in Table 2 because the systems have results from multiple markets that are similar in nature and should align.

Conclusion

The results of this study identify differences in the abilities of technical trading systems to detect market disequilibrium. While different systems, different markets, and different timeframes could have generated different results, choosing general parameters in this study helped retain a very basic structure for the tests.

The world of computerized trading is ever complex, and the sector of trading is growing today as more and more traders are utilizing the power of artificial intelligence in their trading strategies. If an investor could hypothetically produce a system that trades autonomously and is statistically profitable, such a system could dominate the trading world moving forward as technology develops and evolves more and more.

Several large biases exist in this study that must be addressed, and which warrant a retest of these systems to achieve true, more accurate results.

i. Data bias: The optimization practices of the tests were flawed. The systems were applied to a timeframe of 10 years and parameters were optimized on the entire period, never being walked forward. They were not introduced to new data via walk-forward analysis. This fundamental step in analyzing the performance of technical indicators was overlooked in these tests for a couple reasons. Firstly, lack of experience with Tradestation programs and the research method itself required a tremendous learning curve on the part of the author of this study. Not to mention that this test had a completion deadline (as an undergraduate thesis project) which limited the depth to which the study could extend to.

ii. Issues with optimization practices: Considering the partially flawed optimization practices mentioned above, the best fit parameters, for the entire 10-year period, were theoretically not the best results that could have been achieved. This is because the parameters were constrained to 5–25-day lookback periods[7] for most of the systems[8]. Moving forward, a retest should utilize walk-forward analysis, selecting the best parameters of a given set of data (a time period) and using those parameters on unseen data (the next year following the test period. The process should be repeated for each of the years or defined periods in the selected timeframe.

iii. Biases in trade entry: Yet another issue with the tests, the systems were calculated using end-of-day price data. More critically, this led to all positions being entered just after the close of each day[9], which is not how trading occurs. This presented an issue with the tests because the system requires input by the trader to define how soon positions can be entered after a signal has occurred. In this particular case, a simple solution would be to enter at market open on the next trading period. More sophisticated systems would most likely include shorter timeframes for signal generation and multiple positions could be entered/exited on the same day. This would need to be addressed in future tests.

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[7] The lookback period in this instance simply refers to the number of bars used in the calculation of the trading indicator. For example, a simple moving average requires a defined length of bars to be used in the moving average value calculation.

[8] Not all systems require a length of bars for a lookback period. For example, a channel system may only require a standard deviation calculation and is not dependent upon moving average price data.

[9] In the systems, the trades would be placed at 2:20 ET each time a new position was entered. The normal trading day for all three grain markets ends at 2:20 pm ET.

iv. System bias: The systems used in the project were pulled directly from Tradestation's platform and were minimally tweaked, with respect to input parameters and properties. This was because of the original intent of choosing industry standard technical indicators to perform the testing procedures. Any individual trader would likely select other systems or utilize a self-produced system to test for market disequilibrium. For this study, we chose to implement simple, generic technical indicators to test because they are widely utilized by many market participants, *not just computerized, algorithmic traders*. For example, a trader who uses a simple moving average in his or her trading commentaries, recommendations, or other services should find value in a test like this to determine the ability of such an indicator to generate profitable signals over time.

Regarding the accuracy of these tests it must be noted that a retest of these results must take place for a more accurate picture. In summary, this work merely presents a framework for retests to take place. In fact, one very positive implication of this study is the process that this helps define (with respect to backtesting trading strategies and the implications to managing financial capital). As for the project itself, this should help serve as a guide to future tests in this field. The reader of this paper may walk away with a better view on what not to do when performing similar tests or retests. Nonetheless, this paper could still prove a helpful reference in evaluating disequilibrium in futures markets, assessing the profitability of technical trading systems, and perhaps quantifying biases in applying systems to trading financial instruments.

Appendix I:

Return Retracement Ratio

The return retracement ratio is a performance evaluation metric that measures return/risk. It is calculated by dividing the average annualized compounded return (R) by the average maximum retracement measure (AMR):

$$\text{RRR} = \frac{\text{R}}{\text{AMR}}$$

$$\text{AMR} = \frac{1}{n}\sum_{i=1}^{n} MR_i$$

Where n = number of months in the survey period,

$$MR_i = \max\,(MRPP_i, MRSL_i)$$

Where,

$$MRPP_i = \frac{PE_i - E_i}{PE_i}$$

$$MRSL_i = \frac{E_i - ME_i}{E_i}$$

Where,

E_i = equity at end of month *i*

PE_i = peak equity on or prior to month *i*

ME_i = minimum equity on or subsequent to month I

R is the average annual compounded return calculated by:

$$R = \sqrt[n]{E/S} - 1$$

Where

S = starting equity

E = ending equity

N = number of years

(Mencken)(Signal Trading Group)

The AMR is calculated automatically by Tradestation to reflect the maximum drawdown for each position, using the closing prices for each day, the same data used for generating trade entry/exit signals. The ratio was first introduced by Jack Schwager to expand on the Sharpe Ratio.

RINA Index

The RINA index combines Select Total Net Profit, time in the market, and Drawdown Calculations into a single reward/risk ratio (Tradestation).

$$\text{RINA Index} = \frac{Select\ Total\ Net\ Profit}{(Average\ Drawdown)\ x\ (Percent\ Time\ in\ the\ Market)}$$

A higher K-Ratio is desired. A ratio of 100 or more is a good benchmark for system adversity, 200 or higher is a desirable figure for a system (Inovance).

K-Ratio

The K-Ratio is similar in idea to the Return Retracement Ratio and Sharpe Ratio (not used in this paper) in that it evaluates returns to risk over time. The K-ratio differs in that it uses linear regression techniques to measure the consistency of results through time using a value-added monthly index (VAMI).

$$K - Ratio = \frac{(Slope\ logVAMI\ regression\ line)}{n\ (Standard\ Error\ of\ the\ Slope)}$$

Where VAMI is calculated using the closing prices at the end of each month.

The higher the ratio, the greater the return in relation to risk associated with time (Tradestation).

A ratio greater than 2 is desirable in evaluating system performance.

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