Survival Analysis of Ichimoku Cloud Indicator Benchmarked on the S&P 500 Index

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This paper implements a genetic algorithm of 20 input variables (technical indicators) outlined by the Bank of St. Louis Fed's research department updated to include newly adopted technical indicators Ichimoku cloud. The research is tested over the 1980-2016 period and benchmarked on the S&P 500 Large Cap Index. The hypothesis is to see if investors may gain additional information from using technical indicators in their asset allocation strategy. The results show through stepwise regression that moving averages, and Ichimoku cloud indicators may convey information to investors although there may be additional macro-economic information not picked up by the technical signals that should be included in the system of equations. The results show from 1980-2016 the genetic algorithm strategy produces total return of 3308.31 percent versus the S&P 500 1909.90 percent. The result is .16608 with p-value of 0.000 for the Moving Average 3,12 and 0.24 for Ichimoku Cloud Indicator based on the 1,26 period. For Ichimoku Indicator 26,52 it is 0.000 and for 1,52 0.009.

Keywords: technical analysis, S&P 500, Ichimoku cloud, genetic algorithm, moving averages

INTRODUCTION

This paper uses a step-regression to analyze the results of twenty technical indicators and how well they capture the performance of an S&P 500 investment strategy. This is benchmarked on a naïve buy and hold strategy. The in-sample time period is 1980-2016. Data is from Bloomberg.

The returns are tested over three overlapping time frames. 1980-2016, 2001-2016, 2008-2016. The purpose is to capture the returns if an investor put their money at risk just prior to a recession and held until today, comparing how their portfolio would look compared with a naïve buy and hold. The step regression runs through successful ordinary least squares running the dependent variable (strategy returns) on the 20 technical indicator dummy variables. The indicator variables with a t statistic less than one are removed, and the process is repeated until the remaining indicators are left with a positive test statistic. The strategy returns are updated after each iteration.

The computation of the technical indicators is based not on the raw signals but on the accuracy over a selected period. The short run accuracy of each indicator's "in" signals is summed over 7 trading days. The result is weighted over the medium term accuracy of both "in" and "out" signals summed over 8 trading days. The decision for market allocation is based on evenly weighting a portfolio of 100% exposure over how many signals have an in or out signal on the given trading day. That is, signal for entering the market on a given day is the weighted average of the in or out signals based on the historical "accuracy" of indicators over the given period. After the regression this can be calibrated to improve performance but for the regression and test results 8 and 7 are used for medium and short term respectively. The results are weighted such as this to implement a learning algorithm process that tries to catch market trends based on what the market is responding to. Given the set of technical indicators outlined in the Bank of St. Louis Fed research department's working paper (2008) titled "Forecasting the Equity Risk Premium" with additional indicators from newly adopted eastern techniques (Ichimoku Cloud) and updated daily.

LITERATURE REVIEW

The efficient markets hypothesis states that prices follow a random walk and cannot be predicted based on their past behavior. According to EMH there are three degrees of market efficiency. The strong form states that all public and private information that is known is immediately factored into the market's price. In the semi-strong form, all public information is considered to have been reflected in price. The weak form only holds that the information gained from examining the market's past trading history is immediately reflected in price. Past trading history is public information so anything that violates the weak form also violates the strong and semistrong form. Violations of this are prevalent in literature and are outlined below in the literature review.

Although EMH is widely accepted, there are two approaches to generating returns in the market. Fundamental analysis, and technical analysis. Fundamental analysis ignores mostly the semi-strong and strong forms of EMH. This is more widely accepted by academic literature. Fundamental analysis is more concerned with economics and assumes prices may be predicted based on publicly available economic data, such as yield curves, and earnings announcements. Goyal and Welch (2008) discuss the use of fundamental analysis such as dividend price ratio and interest rate inversion to forecast stock prices. This is outlined further in the literature. Technical analysis accepts the semi-strong form of the EMH that all available public economic data and fundamentals are already priced into the current stock market price. This ignores primarily the weak form of EMH. Technical analysts are more concerned with how past price and volume information may reflect information useful to investors to make investment decisions in the future. Andy Lo (2000), Jasemi et. Al (2012), Blume et al (1994), Menkoff, Schlumberger (2013), Zhu et al (2009), Han, Yang, Zhou (2013), Min et al (2016), Fama and Blume (1966) all test various forms of making stock market predictions based on past information. Violating the weak form of EMH.

This paper extends their literature in providing new technical tools (Ichimoku Cloud) which has been prevalent in Japan since the early part of the last century, but has only recently implemented in western trading. This is used jointly with technical indicators from Neely et. Al (2006); who forecast the equity risk premium using both technical and fundamental analysis. They find that technical indicators provide most current information during business cycle peaks.

Trading costs may reduce any excess returns in the market (Fama 1966), but when updated to the costs of floor traders it is found that some profits may be made (Sweeny 1988).

Moving averages are widely used by practitioners and are recently being included in academic literature. Additional literature, or more in depth look at current literature on technical analysis is below.

Jasemi, Milad, and Ali M. Kimiagari. (2012), note that moving averages are one of the most popular and easy to use tools available for technical analysts. They form the building blocks for other technical indicators and overlays.

Menkhoff, Lukas, and Manfred Schlumberger (2013) states the use of technical analysis seems to be persistently profitable. In response to a positive test statistic they note that personal and institutional risk restrictions limit the ability to fully exploit the theoretical profit potential. Thus arbitrage opportunity exists and the indicators are profitable.

Zhu *et al* (2009) show how an investor might add value to an investment by using technical analysis, especially the MA if he follows a fixed allocation rule that invests a fixed portion of wealth into the stock market (as dictated by the random walk theory of stock prices or by the popular mean-variance approach).

Han, *et al*. (2013) document that an application of a moving average timing strategy of technical analysis to portfolios sorted by volatility generates investment timing portfolios that substantially outperform the buy and hold strategy. For high-volatility portfolios, the abnormal returns, relative to the capital asset pricing model (CAPM) and the Fama-French 3factor models, are of great economic significance, and returns are greater than those from the well-known momentum strategy.

Dai, *et al* (2016) show the optimal trading strategy is a trend following strategy. They show ex ante experiments with market data reveals their strategy is efficient not only in U.S. market (SP500 index) but also in China market (SSE index). They observe an interesting divergence of the performances of the trend following trading strategy with short selling. Adding short selling significantly improves the performance in simulations but the performance in tests using the market historical data is mixed.

McLean and Pontiff (2016) the findings point to mispricing as the source of predictability. Post publication, stocks in characteristic portfolios experience higher volume, variance, and short interest, and higher correlations with portfolios that are based on published characteristics.

Lo, Mamysky, and Wang (2000) propose a systematic and automatic approach to technical pattern recognition using nonparametric kernel regression, and apply the method to a large number of U.S. stocks from 1962 to 1966 to evaluate the effectiveness of technical analysis. By comparing the unconditional empirical distribution of daily stock returns to the conditional distribution – conditioned on specific technical indicators such as head-and-shoulders or double-bottoms, they find over the 31-year sample period, several technical indicators do provide incremental information and may have some practical value.

Blume, Lawrence, Easley, and O'hara (1999) show that volume provides information on information quality that cannot be deduced from the price statistic. They show that traders who use information contained in market statistics do better than traders who do not. Technical analysis then arises as a natural component of the agents' learning process.

Fama and Blume (1966) report there had been a considerable interest in the theory of random walks in stock-market prices. The basic hypothesis of the theory is that successive price changes in individual securities are independent random variables. Independence implies, that the past history of a series of changes cannot be used to predict future changes in any "meaningful" way. The authors test the Alexander filter rule, on a series of equities, subject to trading costs that even floor traders cannot avoid. They find for thirty securities and across a time period of five years the 0.5 per cent filter initiated 12,514 transactions. This is an average of eighty-four transactions per security per year. The transaction costs alone push the returns below that of a buy-and-hold policy, reducing the returns by 8.4 percent. They note to go long when a short signal is received has the effect of reversing the signs of he returns from short positions. Thus the negative annual average return of -.160 on the short positions of the 5 percent filter becomes a positive return of the same magnitude. Thus, if the costs of operating different versions of the filter rule are considered, it seems that even the floor trader cannot use it to increase his expected gains appreciably.

Richard J. Sweeney notes mechanical trading rules seem to have more potential than previous tests found. Fama and Blume (1966), looking at the Dow 30 of the late 1950s, found no profits for the best (1/2-percent) rule after adjusting for transaction costs. The test used in this paper assumes constant risk premia, or more generally, that risk premia are on average approximately the same on days "in" as for the total period. The majority of academic financial economists subscribes to the view that financial markets are at least "weak-form" efficient. Much of the evidence on which these views are based is from serial correlation and filter rule tests of the 1960s on data from the New York and American Stock Exchanges. In the 1970s, empirical work generally dealt with specific models such as the CAPM rather than with market efficiency. Even when the "anomalies" literature arose later in the 1970s, the anomalies were not overly troubling since the transaction costs discounted any opportunity for excess profits. The studies of the 1960s tended to understate filter rule returns relative to buy-and-hold and do a poor job of selecting possible winners. The tests did not have statistical confidence bounds for judging significance. The review of Fama and Blume (1966) shows 15 of the 30 securities they considered seem to offer potential profits for the ½ of 1 percent filter rule over the period 1956-1962. When the 14 available securities from this group are examined over the later period 1970-1982 with a test with statistical confidence bounds, each of these securities gives highly significant profits for a floor trader; for example, an equally weighted portfolio gives profits of over 14 percent per year. The results are sensitive to both transaction costs and to whether the closing price is an unbiased estimate of the price at which one can buy or sell (after taking account of the bid-ask spread). Transaction costs, particularly the opportunity cost of the time and trouble of running the strategy, may be larger than assumed. Further, it is possible that one may systematically end up buying above and selling below the closing price (beyond the account takin above of the bid-ask spread). The interesting issue is why substantial profits still seem to be made at least by floor traders, that is, why the market seems weak-form inefficient at their level of transaction costs. Once a rule is known, a computer program that generates limit orders based on the rule can be created at trivial cost, and for any operation that already uses computers, the strategy can be implemented at negligible marginal cost.

Neely, *et al.* (2014) note technical indicators display statistically and economically significant in-sample and out-of-sample forecasting power, matching or exceeding that of macroeconomic variables. They find technical indicators better detect the typical decline in the equity risk premium near business-cycle peaks, while macroeconomic variables improve equity risk premium near cyclical troughs. They find that combining information from both technical indicators and macroeconomic variables significantly improves equity risk premium forecasts versus using either type alone.

The literature above shows a variety of research types and articles spanning from present to the 1960s. The information gathered shows how filter rules have been used to test the hypothesis of random walk and weak form efficiency on the U.S. stock market. The data is inconsistent but stretches to show how the use of transaction costs, and bid-ask spreads reduce the annual returns and in some cases to the extent where the filter is less profitable than buy-and-hold. More recent analysis shows with transaction costs of floor traders, technical analysis seems profitable and has not been explained why despite having profits the traders have not dried all the profits. The most recent literature extends the use of fundamental analysis (macro-economic variables) to include additional information from technical analysis. Showing how the two types of analysis may benefit investors. The scope of this paper is to test both fundamental and technical techniques, in testing profitability in excess of buy-and-hold on the S&P 500 large cap index. The strategy uses transaction costs of interactive brokers, and slippage of ½ of 1 percent.

Leigh, *et al.* (2001) support the effectiveness of a technical analysis approach of using the "bull flag" price and volume pattern. They use genetic algorithm to determine the subset of their 22 input variables to use to improve the r squared between their neural network estimated price increase and the actual, experienced price increase.

As noted in the literature, technical indicators may be used to capture cyclical business peaks. This study tests 1980-2016 using 20 technical indicators, including those from Neely et. al(2014)and the Ichimoku Cloud indicator. A Genetic algorithm helps to determine the subset of 20 indicators that may be used to improve r squared between the strategy returns and the input variables.

The set of 20 technical indicators used are outlined in Neely et al (2014) but include volume, momentum, and moving average. They are computed from the monthly time frames in Neely et al (2014), and analyzed daily.

Volume

(Linton 2010). P 43-44 notes how Charles Dow was the first to highlight the importance of volume over a century ago. Trends need to be confirmed by higher than normal volume to be taken more seriously. Volume is normally displayed as a histogram at the bottom of a chart, this makes it difficult to get an overall picture of volume. This can be addressed by using a cumulative volume measure such as On Balance Volume (OBV).

On-balance volume (OBV) was discovered by Joe Granville and published in his book Granville's New Key to Stock Market Profits. The indicator is plotted as a continuous, cumulative line. The line is started with an arbitrary number, which rises and falls depending on what the price does. The volume for the day is added in when he price rises and is subtracted when it falls. OBV offers a rough approximation for buying and selling pressure. (Pring, 2002). P 430.

Volume indicators are more closely related to Blume, Lawrence, Easley, and O'hara. These provide a volume momentum strategy for periods defined by the investor. The periods defined are (1,12), (2,9), (3,12). Indicators are constructed monthly for this from daily data.

The inclusion of On-balance volume in Neely et al. (2014) shows a positive test statistic in out of sample performance. That is the relevance in adding it in this paper.

Simple Moving Average

These are used widely in literature and by practitioners. They create a smooth average of price over n periods, defined by the investor. When the price is above the moving average, an investor goes long. If there are two moving averages in sequence, a short, and a long-term average, an investor will take a long position when the short moving average is above the long moving average. These are used in the paper as pairs of (3,12), (2,9), (1,7), (10,52), (1,52), (1,10). The pairs of long and short-term averages are adjusted from monthly periods to daily.

It is evident that trends in stock prices can be very volatile, almost haphazard at times. One technique for dealing with this phenomenon is the moving average (MA). An MA attempts to tone down the fluctuations of any price series into a smoothed trend, so that distortions are reduced to a minimum. A simple MA is constructed by totaling a set of data and dividing the sum by the number of observations. The resulting number is known as the average, or mean average. In order to get the average to "move", a new item of data is added and the first item in the list subtracted. The new total is divided by the number of observations, and the process is repeated. (Pring, 2002). P154

Momentum

MAs are useful, but they identify a change in trend after it has taken place. There are two broad ways of looking at momentum. The first uses price data for an individual series. It is then manipulated in a statistical form that is plotted as an oscillator. This is called price momentum.

The simplest way of measuring momentum is to calculate the rate at which a security price changes over a given time period, this is a ROC indicator, or rate of change. The current price is divided by the price n periods ago. The subsequent reading will be calculated by dividing the next periods price by the price n-1 periods ago. The result is a series that oscillates around a central reference point. The horizontal equilibrium line represents the level at which the price is unchanged from its reading n periods ago. If the ROC calculation were made for a price that remained unchanged, the oscillator would be represented by a horizontal straight line. When ROC is above the reference line, the market price that it is measuring is higher than its previous level. If this is the case, one would go long otherwise, stay out. For this study, ROC periods of 100, 50, 20, 12, and (9,12) are used from daily data. (Pring 2002) p 183.

These do not have any significant out of sample value in Neely et al. (2014) but are included in this test.

Ichimoku

Academic interest in the Ichimoku cloud indicator is a recent occurrence and a developing field of research. The Ichimoku Cloud is somewhat similar to a moving average but as the midpoint of high and low over n periods. The periods defined in this paper are (1,52), (1,26), (1,9), (9,26), also (26,52). Where crossovers denote entry points.

David Linton's book on Cloud Charts (2010) remains the best primer on the use of the Ichimoku Cloud. He also includes a good explanation of technical analysis in the first half of the book.

Lim, *et al.* (2016) explore the profitability of signals using Ichimoku Cloud charts on single stocks in Japan and the U.S. The study analyzed 202 stocks on the Nikkei 225 and 446 stocks on the U.S. markets. They analyzed long and short strategies from 2005-2014. Their study proved that cloud charts generate profitable signals, both long and short, in both countries.

Biglieri and Almeida (2018) conduct a study using the Ichimoku Cloud to forecast the price movements of Facebook in bullish and bearish situations.

Gurrib (2020) uses the Ichimoku Cloud to trade the top ten energy stocks from the S&P Composite 1500 Energy Index. The strategy utilizes long only and short only strategies. The study concludes that the use of the Ichimoku Cloud by experienced traders can protect against market downturns and also provide profitable trading strategies.

The computations for the indicators and the trading rules are available upon request. According to Linton (2010), Cloud charts are increasingly being selected as the chart of choice on trading screens around the world. The charts are a newly discovered form of technical analysis in financial markets, developed towards the end of the last century in Japan, where they are known as Ichimoku.

Similar to moving averages, the construction of cloud charts seeks to smooth out price action. The method is based on taking the midpoint of high and low points over the last 9, 26, and 52 periods. More information on the use and trading rules can be found in David Linton's book, Cloud Charts.

Motivation

Very few technical indicators, if any, consistently outperform the market. Most perform the same, a little worse, or much worse. This is due in part to rapidly changing market conditions. Since the inputs are based on price, they are always slow to move and catch price movement.

Some outperform the market over specific time frames but likely carry larger risk in the process. The motivation behind this research is to capture market trends, and invest in the risk free rate or cash when the market sells off.

Gathering information from several signals and separating those signals proves challenging. That is, choosing which signal to follow, and when, on a non-subjective basis is difficult. The methodology here provides separation from highly correlated variables using look back periods. Dropping nonsignificant variables through step-regression is also a large factor.

METHODOLOGY

The portfolio management and input variables are calculated in Microsoft's excel spreadsheet tool. Statistical software TSP is used for ordinary least squares step-regression. This is the implementation of genetic algorithm for improving model fit.

Data

This study is considered for the S&P500 large cap index adjusted for dividends. The data is found from Bloomberg.

Raw Signals

The raw signals of all twenty input variables are considered. They are then rated on short-term and medium term accuracy.

Correlation of Indicators

The indicators are all based on past price and are highly correlated. Thus, the evaluation is on both short term and medium term accuracy to create some separation between their signals.

Short Term Accuracy

This is the short-term accuracy of "in" signals by each indicator, summed over seven trading days. Accurate in signals is a signal that was given a "buy" at market open, and the market closed non-negative.

Medium Term Accuracy

The set of indicators are rated on accuracy of "in" and "out" signals, summed over eight trading days and grouped by indicator type (volume, momentum, moving average, Ichimoku). If they are also the maximum among their short-term rankings, their current trading signal is recorded.

If multiple indicators have the same maximum value and have their signals recorded the number of buy signals is divided by the number of signals considered. This gives a percentage for market exposure between 0 and 1. An investor may invest on market exposure and invest any amount less than 1 in the risk-free rate.

Risk Free Rate

The Risk Free rate is computed monthly and from the data tables from Albert Goyal's website. For Sharpe ratio computation of annual returns it is assumed to be from the month of November 2016.

The returns covered in this paper do not reflect investing in the risk-free rate, which would improve the strategy. It is possible to benefit investors by investing in the risk-rate of return when not fully invested in the market.

Trading Costs

Transaction costs for entering and exiting the market are considered to be 0.005 per share. This is twice the current rate for Interactive Brokers. It is a reasonable expectation of what high net worth participants may pay.

It is assumed an investor can move freely between the market and the risk free rate of return. Transaction costs are only considered when the investor fully invests in the market or fully invests in the risk free rate.

Entry and Exit at Close

The strategy notes that investors may not be able to enter or exit the market right at the close. Therefore, for entry days the price is taken at the open and evaluated at the close. For holding, the return is calculated by the close of the current day, less the close of the previous day. For exit, the strategy assumes exit at the next trading day's open and evaluated at the close. This method reduces returns and is similar to assuming entry at the current close, and evaluating at the next close.

Slippage

Slippage is assumed to be 0.005 for entry and exit, taken from open and closing prices respectively. In reality this may be different as investors may not be able to act on all information as soon as they receive it.

Genetic Algorithm

A stepwise regression is used to eliminate nonsignificant factors through successive iterations of ordinary least squares dummy variable regressions of the strategy returns on the twenty technical indicator input variables. In plain English, the system seeks to improve adjusted r-squared through removing nonsignificant (t-value <1) indicators through repeated regressions until the remaining results include only significant indicators in predicting returns. Summary statistics are available upon request.

Dummy Variables

Inputs are characterized as dummy variables. Carrying a value of 1 or 0. The strategy returns are regressed on the set of input variables. The names of each input variable are converted to I1-I20 for statistical regression. I1I5 represent momentum strategy, I6-I9 represent volume, I10-I15 represent moving average, and I16-I20 represent Ichimoku. The regression results for 1980-2016 are noted below.

RESULTS

TABLE 1
REGRESSION OUTPUT

Variable	*Coefficient*	*Error*	*t-statistic*	*P-value*
C	-.475705E-02	.167779E-03	-28.3530	[.000]
I10	.629628E-02	.214664E-03	29.3308	[.000]
I17	.475386E-03	.210528E-03	2.25807	[.024]
I19	.240651E-02	.225257E-03	10.6834	[.000]
I20	.671934E-03	.255505E-03	2.62982	[.009]

R-Squared / Regression Results

Adjusted r-squared is recorded for 1980-2016. The result is .16608 with pvalue of 0.000 for the Moving Average 3,12 and 0.24 for Ichimoku Cloud Indicator based on the 1,26 period. For Ichimoku Indicator 26,52 it is 0.000 and for 1,52 0.009. These are the significant factors in producing the returns from 1980-2016. The constant term has a negative test statistic. This means If all indicators were set to zero the strategy would have a negative return.

Market Recessions

Recession periods are identified from the federal reserve bank of St. Louis, peak to trough. For the in-sample study of 1980-2016 the strategy is exposed to 5 recession periods. With an investment in 1980, the strategy underperforms in the recessions of 1980, 1981-1982, and 1990-1991. However, after 2000 the strategy greatly over-performs in 2001 and in 2008. The overlapping study of 2000-2016 is exposed to two recession periods, and 2008-2016 is exposed to one. These later studies outperform.

Strategy Results

For the period of 1980-2016 the indicators with the most information are moving average (3,12) and Ichimoku (1,26), Ichimoku (26,52), and Ichimoku (1,52). These provide the lowest risk solution, among the indicators tested. The results over each time period are recorded below. Equity curves follow the results.
1980-2016

Total Return: 3308.31 percent vs. 1909.90 percent
Average Annual Return: 10.90 percent vs. 9.76 percent
Annual Standard Deviation of Returns: 14.10 percent vs. 15.92 percent
Sharpe Ratio: 77.14 percent vs. 61.17 percent

Analysis of Results 2000-2016

The total return is higher and average annual returns are higher on a risk adjusted basis. Risk free rate is assumed to be the monthly risk free rate from November 2016. The strategy underperforms in 1981, 1982, 1984, 1990, 1994, and leaves the market as a better strategy up until 1999, however after exposure to two recessions after the millennium the strategy out performs the market.

2000-2016
Total Return: 253.67 percent vs. 48.00 percent
Average Annual Return: 8.53 percent vs. 4.03 percent
Annual Standard Deviation of Returns: 13.81 percent vs. 17.58 percent
Sharpe Ratio: 61.64 percent vs. 22.79 percent

Analysis of Results 2008-2016

The average annual return is higher on a risk adjusted basis. The risk free rate is assumed to be the holding period risk free rate for the month of November 2016. The strategy is exposed to two recession periods. It outperforms in 2001 and 2002 but underperforms initially in 2000 and in 2003, while out performing based on annual returns in 2008-2009 and in 2011.

2008-2016
Total Return: 145.41 percent vs. 46.60 percent
Average Annual Return: 11.59 percent vs. 6.48 percent
Annual Standard Deviation of Returns: 16.20 percent vs. 19.25 percent
Sharpe Ratio: 71.43 percent vs. 33.57 percent

Analysis of Returns

The strategy is exposed to one recession period in 2008. From FRED data (Federal Reserve Bank of St. Louis) the peak-to-trough identified recession period is (find this!). The strategy outperforms during this period and the following year, and also 2011. For 2016 year to date the strategy underperforms, which is consistent with the history of this system.

TABLE 2
RETURNS AND SIGNIFICANCE

	Market Ret	*Algo Ret*	*p-value*
2008	47%	140%	15%
2000	64%	303%	5%
1990	512%	1285%	7%
1967	2594%	5800%	14%
1950	10494%	19822%	22%

Equity Curves

Each chart represents the growth of $100 over the respected timeframe. Series 1 is the growth over the investment in the set of technical indicators.

Series 2 is the growth over the naïve buy-and-hold on the benchmark.

FIGURE 1
$1 INVESTMENT FROM 1950

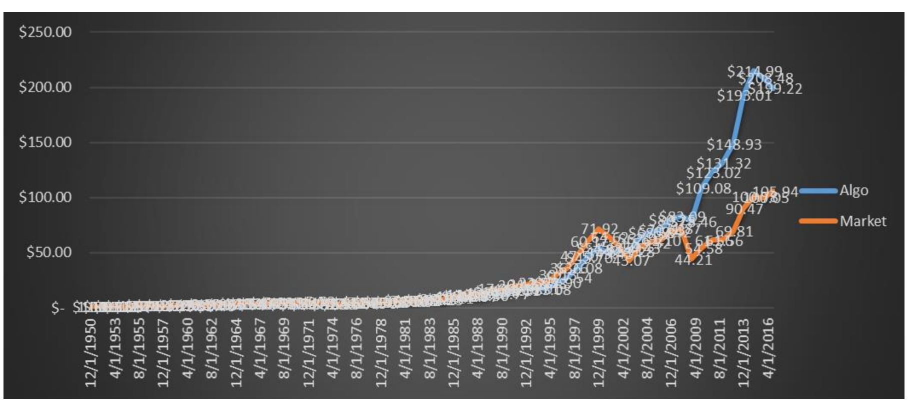
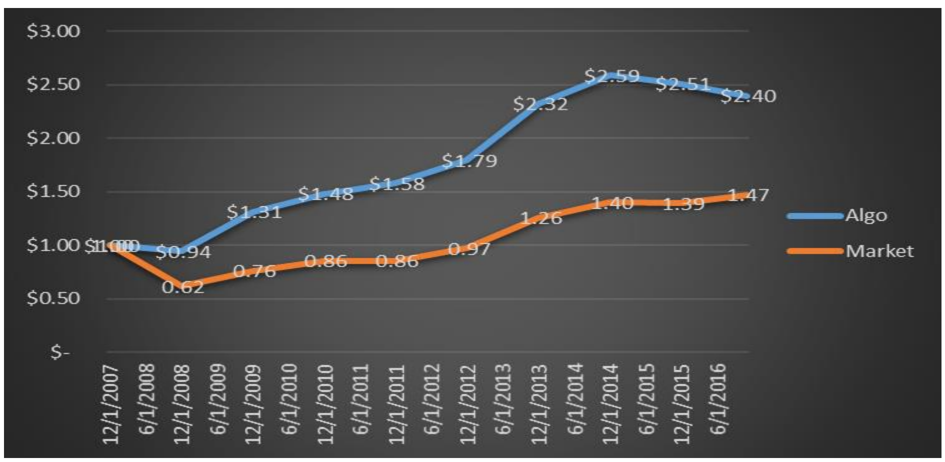


FIGURE 2
$1 INVESTMENT FROM 1999

FIGURE 3
$1 INVESTMENT FROM 2007



CONCLUSION

The strategy of investing based on the weighted average of accurate in and out signals of technical indicators, proves profitable over three overlapping time frames benchmarked on the S&P 500 index. A genetic algorithm shows the resulting indicators are based on moving average and Ichimoku cloud. Other indicators outlined in literature do not hold as much weight with the presence of the Ichimoku cloud indicator and it may be interesting for academic research to explore further. The conclusion shows that the presence of technical indicators may convey information about market timing to investors and may prove to be profitable on a practical level. This study shows through the use of step-wise regression that technical indicators may be useful tools to investors when applied to U.S. stock markets. This research could be expanded to foreign markets and other exchanges. With three different start dates, all within one year of a recession period, and the same end-date (11/20/2016) the strategy based on technical analysis proves better than a buy-and-hold strategy on a risk adjusted basis. This uses information from the Ichimoku cloud, and moving average cross over. Although not better in all years, or in all recession periods it outperforms overall than buy-and-hold and outperforms in the last two recession periods. This violates the weak form of EMH.

This could be tested on the Nasdaq 100 for robustness. Or, it could be expanded to emerging markets. Out of sample returns are currently being tested.

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