Honors College

Spring 2019

# Sunshine on a Cloudy Day: Evidence in Support of a Moving Average Strategy Across Down Markets Using ETFS

John Kay
*University of Maine*

# SUNSHINE ON A CLOUDY DAY: EVIDENCE IN SUPPORT OF A MOVING AVERAGE STRATEGY ACROSS DOWN MARKETS USING ETFS

by

John Kay

A Thesis Submitted in Partial Fulfillment of
the Requirements for a Degree with Honors
(Finance)

The Honors College
University of Maine

May 2019

Advisory Committee:

Matthew Skaves, Lecturer in Finance and Accounting, Advisor
Henri Akono, Assistant Professor of Accounting
Stephen Jurich, Assistant Professor of Finance
Robert Klose, Professor of Biological Sciences, UMAB and Preceptor in the Honors College
Stefano Tijerina, Lecturer in Management

# ABSTRACT

This study is motivated by the theoretical framework that suggests market timing and other algorithmic trading strategies can add value in some aspects of the investment and portfolio management process. This study examines whether a moving average crossover strategy can outperform a buy and hold strategy across a set of stock portfolios.

Although the algorithm used in this study is likely to underperform over the long run, the end-of-year selloff in 2018 revealed that moving average trading strategies add value during down markets. Consistent with Marshall et al. (2012) and Han et al. (2012), this study finds that the performance of the algorithm is amplified by the annual return, standard deviation, and downside deviation of the underlying portfolios of stocks. Where the preceding studies examine stock indices, this study examines exchange traded funds (ETFs) across six categories based on market capitalization: total market, mega cap, large cap, mid cap, small cap, and micro cap. The study finds that the algorithm outperforms the conventional buy and hold strategy across all ETFs during the observed down markets. Additionally, the study finds that the algorithm outperforms the most on the ETFs that experience the greatest selloffs. In conclusion, the study is optimistic about the use of trading algorithms to reduce the impact of market selloffs on investment returns.

# ACKNOWLEDGEMENTS

I would like to express my very great appreciation to the individuals who have supported me in the process of conducting this study. To begin, I would like to offer a special thanks to my advisor, Matt Skaves, for his advice and availability throughout all stages of the project. Next, I am grateful for the assistance given by my committee members, Dr. Henri Akono, Dr. Stephen Jurich, Dr. Robert Klose, and Dr. Stefano Tijerina. It has been a pleasure to work with this team.

I would also like to thank the Maine Business School for a remarkable undergraduate experience, and for providing access to computer labs and statistical software which allowed me to conduct my research. Next, I would like to thank the Honors College for providing the opportunity to compose a Thesis as well as an amazing support staff. Last, I would like to thank my family and friends for supporting me throughout this process.

TABLE OF CONTENTS

# CHAPTER 1

# INTRODUCTION

Throughout the history of the United States equity market, bull markets have lasted about 97 months on average. The current bull market has lasted about 119 months. Throughout the course of this study, the yield curve inverted for the first time since 2007. This study is motivated by the effort to identify trading algorithms that add value during recessionary periods. In doing so, this study examines the performance of a trading algorithm relative to a conventional buy and hold strategy employed on the same set of investments. The investment selection is comprised of the most actively traded Exchange Traded Funds (ETFs) that represent the six categories of the United States equity universe by market capitalization: total market, mega cap, large cap, mid cap, small cap, and micro cap.

The methodology employed in this study is motivated by two studies that divide the United States equity universe into a variety of indices made available by the Center for Research in Security Prices (CRSP). In the first, Marshall, Nguyen, and Visaltanachoti (2012) uses CRSP value-weighted size quintile indices and observes the performance of both moving average and TSMOM strategies across these indices. In the second, Han, Yan and Zhou (2012) examines the impact of return volatility, among other proxies for information uncertainty across stocks, including size, distance to default measure, credit rating, analyst forecast dispersion, and income volatility. The study ranks the performance of trend following strategies employed on each of the deciles within each category. Both

studies find consistent outperformance when organizing the results by the observed variables.

The intention of this study is to apply a similar methodology as Marshall et al. (2012) and Han et al. (2012) to exchange traded portfolios of stocks. In doing so, the study examines a population of 20 ETFs that represent a range of weighted-average market capitalization. Over the period examined in this study, the weighted-average market capitalization of the ETFs corresponded with the level of standard deviation of returns. When comparing the group averages by asset class, the small cap ETFs were consistently more volatile than the large cap ETFs. In fact, when separately ranking the groups by standard deviation and inversely by weighted-average market capitalization, the groups have the same rank in both samples.

With this being the case, the study adheres to the framework that suggests return volatility is demonstrative of information uncertainty, which tends to be higher across smaller companies. Another motivating concept is that the impact of information uncertainty is not lost when stocks are organized into portfolios. Market capitalization corresponds to return volatility throughout the period examined, allowing the study to use these factors as proxies for information uncertainty during this period. In doing so, this study examines the impact of information uncertainty on the performance of the trading algorithm relative to the conventional buy and hold strategy across the ETF population. The study examines the relationship between variables such as annual return, standard deviation, and downside deviation, and the relative performance of the trading strategy.

The study finds that the performance of the trading algorithm relative to the conventional buy and hold strategy is positively correlated with all three of these variables.

For example, the more volatility experienced by the buy and hold strategy, the better the algorithm performs relative to the buy and hold strategy. The same is true with downside volatility and to the greatest degree, annual returns. Additionally, during periods of heightened market selloffs, the algorithm outperforms the most on ETFs that experience the worst selloffs. In the 1-year period observed, the mid cap, small cap, and micro cap ETFs were the most volatile and experienced the worst selloffs. This allowed the trading algorithm to outperform the buy and hold strategy to a greater degree than the larger, less volatile ETFs. In conclusion, the study is optimistic about the idea of employing a moving average trading strategy in late stages of the market cycle. In the event of a market selloff, the strategy would provide downside protection which would benefit the investor the most across his/her riskiest investments.

# CHAPTER 2

# LITERATURE REVIEW

Researchers have long debated the efficacy of technical analysis. Technical analysis is a trading discipline that involves the evaluation of mathematical trends gathered from trading activity, such as price movement and volume, to identify trading opportunities. The discipline is made up of a large collection of trading strategies that vary in complexity and popularity. Our research begins with the work of Brock, Lakonishok and LeBaron (1999). The 1999 study examines a population of 26 technical trading strategies divided into two general categories: moving averages and trading-range breakouts. Brock et al. (1999) defines these two categories as the simplest and most widely used technical trading rules. Our study is primarily concerned with moving averages. In summary, Brock et al. (1999) supports the empirical research suggesting that technical trading rules maintain some level of predictive power.

Chang, Ilomaki, Laurila, and McAleer (2018) illustrate how the size of the trailing windows used in moving average trading strategies impacts financial performance when risk is measured. Observing that the performance of the trading strategy improved, on average, when the rolling window was expanded, Chang et al. supports the predictability of stock returns in the long run. Tapa, Yean, and Ahmad (2016) illustrate the performance of a variety of modified and unmodified moving average trading strategies on the Malaysian equity market. The study suggests that the original MA crossover strategy outperforms the conventional buy and hold strategy based on return, risk-adjusted return

(higher Sharpe ratio) and minimal drawdown, supporting the idea that trend following strategies can enhance investment returns. Since the early 21st century, there have been numerous other studies that support the efficacy of trend following strategies in enhancing investor returns (Brown and Jennings, 1989; Wilcox and Crittenden, 2009; Zhu and Zhao, 2009; Neely et al., 2014).

Despite the results of these studies, there is a body of research that suggests the predictability traits observed in the 2018 study and the returns observed in the 2016 study are anomalistic and not representative of most situations. In fact, these studies are recent examples of a debate that originated in the 1960s with the development of the "random walk" and "efficient market hypothesis (EMH)" framework (Malkiel and Fama, 1970). This framework suggests that asset prices change based on the release of new information. As the flow of information is random, the corresponding price changes are random, and thus follow a "random walk." Advocates of this theory argue that all past information is reflected in an asset's price, leaving no opportunity for investors to earn above-average returns through the examination of past price information alone. Thus, at the weak form of market efficiency, advocates in favor of the EMH framework suggest technical analysis adds no value to investment strategies.

Fama and Blume (1996) finds that technical analysis and the related concept of market timing are unsuccessful in generating excess returns. Olson (1999) suggests that the ability to generate statistically significant excess returns in the currency markets through the use of moving average trading strategies has been eliminated over time. Further, Hutchinson and O'Brien (2014) illustrate that trading rule profits suffer by a substantial margin relative to the conventional buy and hold strategy, when employed in periods

immediately following recessions. Sullivan et al. (1999) employ an advanced bootstrapping methodology to observe the data-snooping bias of past studies. They conclude that preceding studies in support of technical analysis are guilty of data snooping bias, and that moving average strategies do not outperform conventional buy and hold strategies after considering transaction costs.

However, as demonstrated by Chang et al. (2018) and Tapa et al. (2016), the debate that originated in the 1960s is still a point of contention for researchers today. Additionally, it is important to note that the debate does not exist solely in financial economic literature. Major brokerage firms often publish commentaries based on technical analysis, while prominent traders employ technical analysis in some aspect of their trading decisions (Shwager, 1995).

Despite all these studies to the contrary, there is a body of literature that contends that technical trading strategies do add value to the investment process in a variety of ways. For example, Wilcox and Crittenden (2009) are optimistic about the use of trend following trading techniques, and they illustrate a strategy that yields significant return on average. In a 2009 study, Zhu and Zhou (2009) examine the moving average rule and provide theoretical justification for investors to consider it in their asset allocation strategies. The study concludes that investors can add value to their asset allocation strategy through using technical indicators such as moving averages.

Additionally, a study composed by Neely et al. (2014) is optimistic about the use of technical indicators to aid the process of forecasting the U.S. equity risk premium. Neely et al. (2014) notice the fact that historical research favors the use of macroeconomic variables to accomplish this goal, while little attention is paid to the use of technical

indicators. In reality, there is range of practitioners that employ both approaches (Shwager, 1995). Neely et al. (2014) illustrates that technical indicators display statistically and economically significant in-sample and out-of-sample forecasting power, matching or exceeding that of macroeconomic variables. The study observes that, "technical indicators better detect the typical decline in the equity risk premium near business-cycle peaks, while macroeconomic variables more readily pick up the typical rise in the equity risk premium near cyclical troughs," and concludes that when information from both technical indicators and macroeconomic variables is combined, it significantly improves equity risk premium forecasts versus using either type of information alone.

Hutchinson and O'Brien (2014) were among the first to illustrate the performance of trend following trading strategies in periods during and after recessions. As observed by the study, trend following performance tends to be weak for the first four years after a global financial crisis on average (Hutchinson and O'Brien, 2014). In fact, the study indicates that in periods following financial crises, the average returns of trend following strategies are less than half of those in no-crisis periods. Further, in the first twenty-four months following the start of a crisis, trend following strategies produce nearly one third of the return earned in no-crisis periods. Although the intention of the study is to suggest environments in which trend following strategies underperform, the study allows the optimistic market technician to alter his/her trading strategy to account for the new research, and perhaps convert to a buy and hold strategy during the first few years after a global recession.

In a study, Olson (1999) examines the decline of moving average trading rule profits used in the currency markets over the period from 1971 to 2000. His results indicate

that risk-adjusted trading rule profits declined by an average of over 3% in the late 1970s and early 1980s to about zero in the 1990s. Further, the results show that the trading rules produced statistically significant risk-adjusted profits in the 1970s, positive but often statistically insignificant profits in the 1980s, and essentially zero profits in the 1990s. The study suggests that market inefficiencies reported in previous studies may have been only temporary inefficiencies.

The intent of Olson (1999) is to illustrate that the statistically significant excess returns once observed by moving average strategies have essentially disappeared over time. When analyzing empirical research on technical analysis, it is important to distinguish the type of strategies examined in each study. For example, the results observed by Olson (1999) were generated by a set of trading strategies that relied on the calculation of simple moving averages. As suggested by their name, simple moving averages are relatively simple in design. They are calculated by finding the mean price of an asset over a set of preceding days. Although they demonstrated statistically significant returns for investors through the 1970s, their performance has significantly waned throughout the 1980s and 1990s.

To date, given the amount of research both for and against technical trading strategies, it remains inconclusive as to whether or not trades based on technical indicators can provide value to investors. Even Sullivan et al. (1999), which sought to answer the call of Merton (1987) for an effective remedy to control for the data-snooping biases present in the observation of trading strategy performance, has its flaws. Within the study, Sullivan et al. (1999) illustrate a capable, multi-factor bootstrap methodology and apply it to the 26 technical trading rules suggested by Brock, Lakonishok, and LeBaron (1992), and illustrate

that the results of the 1992 study appear to be from data-snooping. They expand the population of 26 trading rules to a universe of 7,846 trading rules and conclude that the moving average trading rules that the study examines do not outperform the conventional buy and hold strategy after the consideration of transaction costs.

Although Olson (1999) and Sullivan et al. (1999) conclude against the ability to generate excess returns by using moving average strategies, the optimistic market technician may interpret the results of the two studies as motivation to continue innovating new strategies, rather than relying solely on historically successful ones. Inadvertently, the studies might encourage the optimistic market technician to take full advantage of any proprietary trading strategies he or she might have, as the value added by such strategies may not last forever.

Illustrating the growing complexity of approaches to technical analysis, Jegadeesh and Titman (2000) applies modern computational algorithms with more effective pattern recognition capabilities to assess the efficacy of technical analysis. More specifically, the study uses smoothing techniques such as nonparametric kernel regression to capture the essence of technical analysis, which is defined as the identification of "regularities in the time series of prices by extracting nonlinear patterns from noisy data." Jegadeesh et al. (2000) find that certain technical patterns, when applied to a population of stocks over a variety of time periods, do provide incremental information. The study does not imply that technical analysis can be used to generate "excess" trading profits, but rather it raises the possibility that technical analysis can add value to the investment process. Noting the continuous advances in statistical learning theory, Jegadeesh et al. (2000) suggest that

technical analysis may be the next frontier for the successful application of pattern-recognition algorithms used to optimize specific objective functions.

Consistent with Brock et al. (1992), Sullivan et al. (1999), and Jegadeesh et al. (2000), certain trend following strategies maintain, at a minimum, some impermanent degree of predictive capability. However, as suggested earlier, Sullivan et al. (1999) and the majority of related studies that precede 2012, have one flaw that we are attempting to examine throughout this study, which is the fact that they are limited to the sole examination of large cap stock indices. For example, Brock et al. (1992) illustrates the performance of moving average strategies on the Dow Jones Industrial Average (DJIA).

However, there is a theoretical basis for the assumption that trend following strategies should outperform on portfolios that represent other than large cap stocks. This assumption is based on principles surrounding the ability of moving average strategies to capture price continuation, and the degree to which small cap stocks are less efficiently priced than large cap stocks. To explain the latter, Zhang (2006) illustrates that information uncertainty can be measured by the standard deviation of returns, which leads to more often periods of short-term price continuation. Further, the study finds that in the case of greater information uncertainty, there will be a higher level of underreaction to public information by investors, and thus a higher level of stock price continuation.

Bhushan (1989) presents a simple model of analyst following and illustrates that analysts focus primarily on large cap stocks. Hong, Lim, and Stein (2000) support the hypothesis that firm-specific information diffuses slowly across the investing public. Further, the study illustrates that momentum strategies work better on stocks with low analyst coverage, suggesting that "stocks with lower analyst coverage should, all else

equal, be ones where firm-specific information moves more slowly across the investing public" (Bhushan, 1989). Smaller companies tend to be less widely followed by professional analysts.

Marshall et al. (2012) and Han, Yan and Zhou (2012) are motivated by the same framework but examine portfolios of stocks rather than individual stocks. The majority of preceding empirical studies focus on large stock indices or populations of individual stocks. The two 2012 studies use a variety of indices made available by the Center for Research in Security Prices (CRSP) to divide the equity universe into certain categories. For example, Marshall et al. (2012) uses CRSP market value-weighted size quintile indices and observes the performance of both moving average and TSMOM strategies across these indices. Han, Yan and Zhou (2012) test the impact of volatility on trading strategy performance, using multiple proxies to demonstrate information uncertainty across stocks, including size, distance to default measure, credit rating, analyst forecast dispersion, and income volatility. The study ranks the performance of trend following strategies employed on each of the deciles within each category. Both studies find consistent outperformance when organizing the results by the observed variables.

The CRSP indices are excellent for research purposes as they represent even distributions of the United States equity market. For this reason, they are often utilized in empirical literature for the cross-sectional examination of the United States equity market. However, this study examines exchange-traded portfolios of stocks (ETFs) and seeks to determine if the results are consistent with a different type of stock portfolio.

Thus, the intent of this study is to examine the performance of the algorithm across a more liquid and actively traded population of ETFs. In doing so, this study uses market

capitalization and standard deviation of returns as proxies for information uncertainty and observes the influence of information uncertainty on the performance of the algorithm relative to the conventional buy and hold strategy. In order to represent information uncertainty, this study uses a testing population of the most actively traded core equity ETFs across a range of weighted average market capitalization. We categorize the sample into groups based on market capitalization, including mega cap, large cap, mid cap, small cap, and micro cap. If one were to separately rank the groups from largest to smallest in terms of weighted average market capitalization, and then from least to greatest in terms of average annual standard deviation over the period used in this study, the groups would have the same rank in both observations. In other words, the largest group of ETFs in terms of weighted average market capitalization, was also the least volatile over the past 11 years, whereas the smallest group of ETFs was the most volatile.

We then run a variety of linear regressions to determine factors that may be driving the performance of the trading algorithm relative to the conventional buy and hold strategy. We do this by observing the annual returns, standard deviation, and downside deviation of the buy and hold strategy, and testing the level of correlation between these variables and the relative performance of the trading algorithm. For example, the study attempts to determine the impact on the relative performance of the algorithm when the buy and hold strategy experiences periods of heightened standard deviation. Within those periods, we then examine the ETFs that did the best.

For simplicity, the strategy employs a 10-day exponential moving average (EMA) which is a proxy for a two-week trading period, and a 50-day moving average, which is a commonly used proxy for a two-month trading period. Specifically, this study examines

the performance of the algorithm relative to a conventional buy and hold strategy employed on the same set of assets and observes the sensitivity of these returns to factors like market capitalization and return volatility.

# CHAPTER 3

# HYPOTHESIS

The overarching hypothesis of the study suggests that a moving average crossover strategy can outperform a conventional buy and hold strategy during down markets, and that the outperformance during those periods is magnified by the level of information uncertainty across the investments being tested. In order to examine this hypothesis, the study develops two levels of hypotheses, with three hypotheses in each level. For simplicity, this study refers to the algorithmic trading strategy as the In&Out strategy, while referring to the conventional buy and hold strategy as the Buy&Hold strategy. The study lists the hypothesis below.

**Table 1.** Level 1 Hypothesis Testing

| Hypothesis | Variables | Null Hypothesis |
|---|---|---|
| $H_1$: In&Out $_{\mu}$ – Buy&Hold $_{\mu}$ < 0 | μ: annual return | $H_{01}$: In&Out $_{\mu}$ – Buy&Hold $_{\mu}$ = 0 |
| $H_2$: In&Out $_{\sigma}$ – Buy&Hold $_{\sigma}$ < 0 | σ: std. dev. of returns | $H_{02}$: In&Out $_{\sigma}$ – Buy&Hold $_{\sigma}$ = 0 |
| $H_3$: In&Out $_{\delta}$ – Buy&Hold $_{\delta}$ < 0 | δ: down. dev. of returns | $H_{03}$: In&Out $_{\delta}$ – Buy&Hold $_{\delta}$ = 0 |

In the first-level, one hypothesis ($H_1$) supposes that the mean return of the In&Out strategy will be less than the mean return of the Buy&Hold strategy. In this case, the null hypothesis ($H_{01}$) supposes that the mean returns of the two strategies will be equal, meaning that the trading algorithm would neither outperform nor underperform the Buy&Hold strategy on average.

The second hypothesis ($H_2$) supposes that the average standard deviation of the In&Out strategy will be less than the average standard deviation of the Buy&Hold strategy. In this case, the null hypothesis ($H_{02}$) supposes that the mean standard deviation of the two strategies will be equal, meaning that the trading algorithm would neither reduce nor increase the standard deviation experienced by the Buy&Hold strategy on average.

The third hypothesis ($H_3$) supposes that the average downside deviation of the In&Out strategy will not be less than the average downside deviation of the Buy&Hold strategy. In this case, the null hypothesis ($H_{03}$) supposes that the mean downside deviation of the two strategies will be equal, meaning that the trading algorithm would neither reduce nor increase the downside deviation experienced by the Buy&Hold strategy on average. The study uses a series of difference tests to evaluate these hypotheses.

**Table 2.** Level 2 Hypothesis Testing

| **Hypothesis** | **X** | **Y** | **Null Hypothesis** |
|---|---|---|---|
| $H_A$: $\rho$ (X,Y) < 0 | Buy&Hold $_\mu$ | Relative Return | $H_{0A}$: $\rho$ (X,Y) = 0 |
| $H_B$: $\rho$ (X,Y) > 0 | Buy&Hold $_\sigma$ | Relative Return | $H_{0B}$: $\rho$ (X,Y) = 0 |
| $H_C$: $\rho$ (X,Y) > 0 | Buy&Hold $_\delta$ | Relative Return | $H_{0C}$: $\rho$ (X,Y) = 0 |

The second-level of hypotheses in this study investigates the correlation between relative performance of the algorithm and factors like annual return, standard deviation, and downside deviation of the Buy&Hold strategy. Here, one hypothesis ($H_A$) supposes that a negative correlation exists between the annual returns of the Buy&Hold strategy, and the relative performance of the In&Out strategy. The null hypothesis ($H_{0A}$) supposes that there is no correlation between these variables.

The second hypothesis ($H_B$) supposes that a positive correlation exists between the standard deviation of the Buy&Hold strategy, and the relative performance of the In&Out strategy. The null hypothesis ($H_{0B}$) supposes that there is no correlation between these variables.

The third hypothesis ($H_C$) supposes that a positive correlation exists between the downside deviation of the Buy&Hold strategy, and the relative performance of the In&Out strategy. The null hypothesis ($H_{0C}$) supposes that there is no correlation between these variables. The study uses a series of linear regressions to determine if significant correlations between these variables exist.

# CHAPTER 4

# METHODS

In this section, the study examines the methodology employed throughout. First, it examines the types of trading strategies employed. Then, it illustrates how the back-testing model used in the study was developed. Then, the study defines its testing population, along with the methodology employed to create it. Finally, the study introduces the variables that are then analyzed in the Results section.

## Moving Average Trading Strategy

Moving average trading strategies are trend-following in nature, as they determine transaction signals by averaging the price of an asset over certain periods (trailing windows) of time. The moving average rule of Gartley suggests that when an asset's current price rises above (falls below) that of its average price over some trailing window, the asset is considered to be in an up (down) trend, and thus the investor should buy (sell) the asset.

The strategy employed in this study is a moving average crossover strategy. A moving average crossover strategy calculates two moving averages with different lengths and determines transaction signals based on their convergences and divergences. The two moving averages used in this trading strategy include a long-period moving average of 50 days and a short-period moving average of 10 days. The 50-day moving average is a commonly used proxy for a 2-month trading period, while the 10-day moving average is a commonly used proxy for a 2-week trading period. When the short-period moving average

rises above (falls below) that of the long-period moving average, the underlying asset is considered to be in an up (down) trend, and thus the investor should buy (sell) the asset. Effectively, the strategy suggests that when the average price of the asset over the last two weeks is greater (less) than the average price of the asset over the last two months, it is time to buy (sell) the asset. Shorter trailing windows are often referred to as fast moving averages as they respond quicker to recent price action. The longer trailing windows are referred to as slow moving averages.

**Chart 1.** Moving average crossover strategy & signals

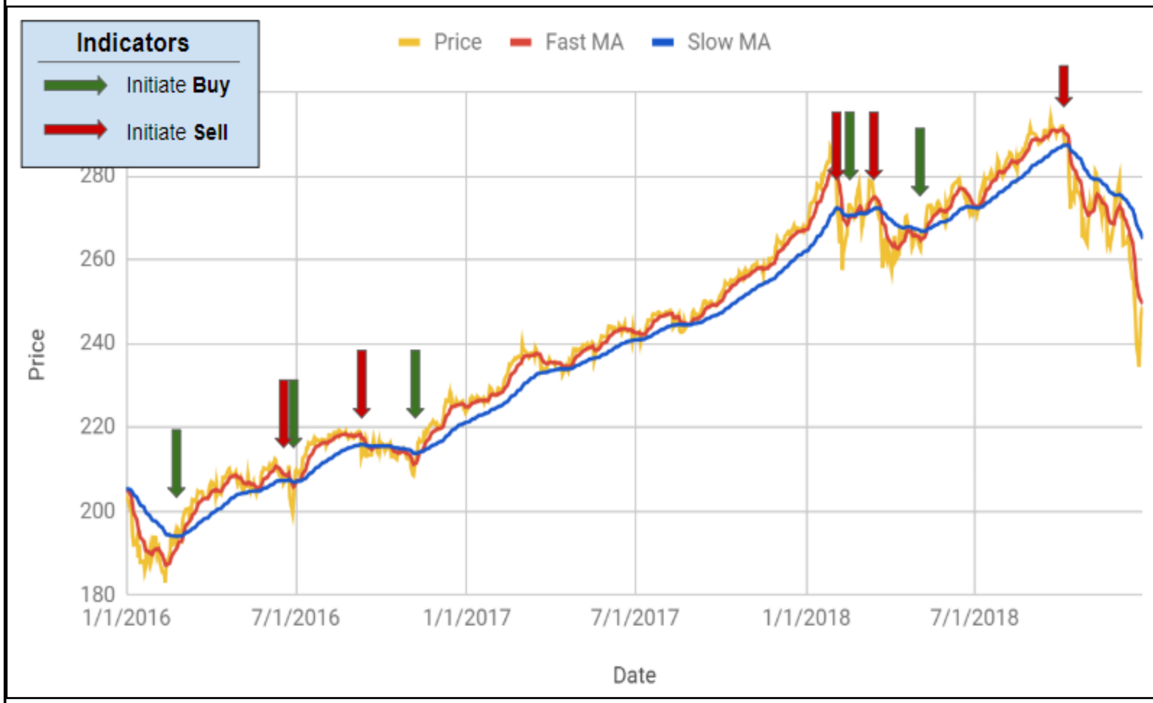



Chart 1 displays the closing price of SPY, the SPDR S&P 500 ETF, in yellow. The red line illustrates a 10-day, fast moving average, and a 50-day, slow moving average. When the fast moving average crosses above(below) the slow moving average, the algorithm will initiate a buy(sell) order at the following day's market open. The buy signal is illustrated by the green arrow, while the sell signal is illustrated by the red arrow.

**Chart 1** illustrates the SPDR S&P 500 ETF (SPY) over a three-year period. The yellow line is the closing price of the SPY, while the red line is a 10-day moving average and the blue line is a 50-day moving average. The green arrows indicate when the short-

period moving average crosses above the long-period moving average, which indicates a buy signal. The red arrows indicate when the short-period moving average falls below the long-period moving average, which indicates a sell signal.

Simple moving averages are calculated by finding the arithmetic mean of a price over a trailing period of time. However, the moving averages used in this study are a category of moving averages called exponential moving averages (EMAs) and are calculated differently. Rather than using the arithmetic mean, and thus equally weighting all days within a trailing window, exponential moving averages more heavily weight recent trading days. Effectively, they suggest more emphasis as to what investors are doing at the moment. As Marshall et al. (2012) illustrated that moving average strategies outperform time series momentum strategies due to their ability to respond quicker to recent price action, we were motivated to apply this version of a moving average strategy that might do so even more effectively.

## Model Creation

The back-testing model developed for this study was built in Google Sheets. The model uses the Google Finance function to dynamically extract price data for any exchange-traded security entered. In order for the algorithm to run, the user enters a security's ticker symbol and chooses a 10-year testing period. Illustrated by **Figure 1**, the model uses the Google Finance function to recall the price history of the entered security over the 10-year period. The Google Finance functions for open price and close price are located in cells CH4 and CJ4 respectively, and they output the price data in columns CI and CK respectively. The moving averages are calculated based on closing prices, but when

buy and sell signals are determined, the transactions are executed at market open the following day. The screenshot below displays the Google Finance function.

**Figure 1.** Google Finance Function

fx =googlefinance(CJ2,CK2,CL2,CM2)

| | CH | CI | CJ | CK | CL | CM | CN | CO |
|---|---|---|---|---|---|---|---|---|
| 1 | Fund | Attribute | Fund | Attribute | Start Date | End Date | 10-day Multiplier | 50-day Multiplier |
| 2 | IWC | Open | IWC | Close | 12/31/2008 | 12/31/2018 | 18.18% | 3.92% |
| 3 | | | | | | | | |
| 4 | Date | Open | =googlefinance(CJ2,CK2,CL2,CM2) | | Short SMA | Long SMA | Short EMA | Long EMA |
| 5 | 12/31/2008 | 30.44 | 12/31/2008 | 31.85 | | | | |
| 6 | 1/2/2009 | 31.7 | 1/2/2009 | 32.02 | | | | |

Figure 1 illustrates how the model uses the Google Finance function in cells CJ and CH to output a security's daily open price in column CI, and daily closing price in column CK, over the 3-year time period suggested in cell CL2 through CM2.

Next, we will describe how the back test model calculates EMAs. When calculating EMAs, it is first necessary to determine the smoothing constant based on the number of days in the trailing window.

$$Smoothing\ Constant = \frac{2}{(Days + 1)}$$

The smoothing constant, also known as an exponential multiplier, for the 10-day period is demonstrated below in **Figure 2.**

**Figure 2.** Calculating smoothing constant

fx =2/(10+1)

| | CK | CL | CM | CN | CO | CP | CQ | CR |
|---|---|---|---|---|---|---|---|---|
| 1 | Attribute | Start Date | End Date | 18.18% × ultiplier | 50-day Multiplier | | | |
| 2 | Close | 12/31/2008 | 12/31/2018 | =2/(10+1) | 3.92% | | | |
| 3 | | | | | | Algorithm Signal | | |
| 4 | Close | Short SMA | Long SMA | Short EMA | Long EMA | In/Out Position | Signal | Transaction Price |
| 59 | 25.29 | 24.84 | 27.01 | 24.48 | 27.25 | -2.77 | | |
| 60 | 27.15 | 25.38 | 26.91 | 24.96 | 27.24 | -2.28 | | |
| 61 | 26.07 | 25.59 | 26.79 | 25.16 | 27.20 | -2.03 | | |
| 62 | 26.68 | 25.84 | 26.70 | 25.44 | 27.18 | -1.74 | | |

Figure 2 illustrates how the model calculates the smoothing constant for the 10-day moving average in cell CN2, and for the 50-day moving average in cell CO2.

$$EMA_{Today} = (Price_{Today} * \left(\frac{Smoothing}{1 + Days}\right) + EMA_{Yesterday} * (1 - \left(\frac{Smoothing}{1 + Days}\right))$$

Illustrated by **Figure 3,** the model then determines the 10-day and 50-day exponential moving averages in columns CN and CO respectively.

**Figure 3.** Calculating exponential moving average (EMA)

fx =CK61*$CN$2+CN60*(1-$CN$2)

| | CK | CL | CM | CN | CO | CP | CQ | CR |
|---|---|---|---|---|---|---|---|---|
| 1 | Attribute | Start Date | End Date | 10-day Multiplier | 50-day Multiplier | | | |
| 2 | Close | 12/31/2008 | 12/31/2018 | 18.18% | 3.92% | | | |
| 3 | | | | | | Algorithm Signal | | |
| 4 | Close | Short SMA | Long SMA | Short EMA | Long EMA | In/Out Position | Signal | Transaction Price |
| 59 | 25.29 | 24.84 | 27.01 | 24.48 | 27.25 | -2.77 | | |
| 60 | 27.15 | 25.38 | 26.91 | 24.96 | 27.24 | -2.28 | | |
| 61 | 26.07 | 25.59 | 26.79 | 25.16 | 27.20 | -2.03 | | |
| 62 | 26.68 | 25.84 | 26.70 | CN61 25.16 × 44 | 27.18 | -1.74 | | |
| 63 | 27.92 | 26.31 | 26.66 | =CK61*$CN$2+CN60*(1-$CN$2) | 27.21 | -1.32 | | |
| 64 | 26.89 | 26.51 | 26.59 | 26.07 | 27.19 | -1.12 | | |

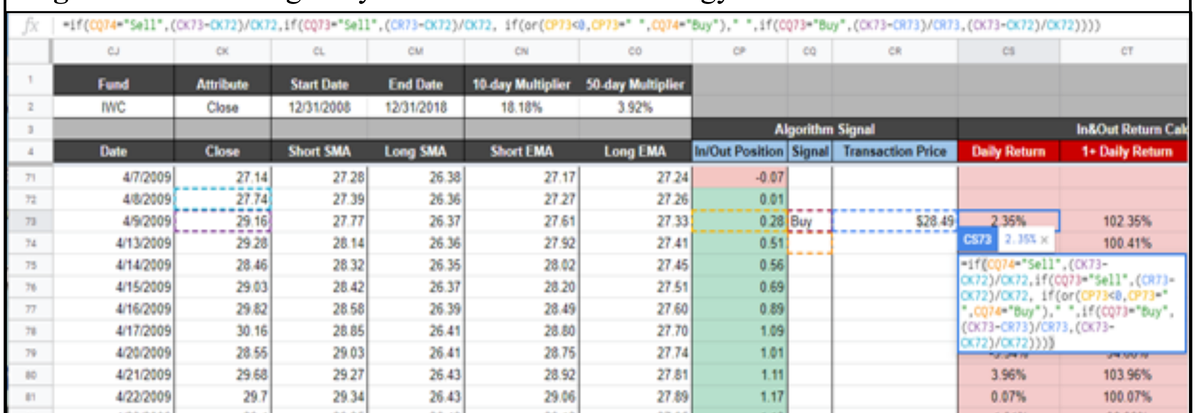
Figure 3 illustrates how the model calculates exponential moving averages in columns CN and CO based on the closing price data found in column CK. The short period moving average is found in column CN, and the long period moving average is found in column CO.

Next, we will describe how the model uses the moving averages to determine when to enter and exit positions. Illustrated by the image above, in column CN and CO, the short (10-day) and long (50-day) exponential moving averages are calculated. Illustrated by the

image below, the columns CP through CR serve as the signal for the algorithm. By subtracting the long-period EMA from the short-period EMA, column CP identifies whether the underlying asset is in an up or down trend. If the difference between the short-period EMA and the long-period EMA is positive (negative), the underlying asset is in an up (down) trend and the strategy should be in (out of) position. Column CQ determines when there is a crossover and distinguishes what type of transaction will be executed. Then, column CR identifies the signal and extracts the price at which the transaction will be executed, based on whether it is a buy or a sell.

The most complex function used in the model is illustrated in **Figure 4**. Column CS uses the signals displayed in columns CP through CR to determine when the algorithm is in position, and thus when to start and stop calculating daily returns.

**Figure 4.** Calculating daily returns for In&Out strategy



```
=if(CQ74="Sell",(CK73-CK72)/CK72,if(CQ73="Sell",(CR73-CK72)/CK72, if(or(CP73<0,CP73=" ",CQ74="Buy")," ",if(CQ73="Buy",(CK73-CR73)/CR73,(CK73-CK72)/CK72))))
```

| | CJ | CK | CL | CM | CN | CO | CP | CQ | CR | CS | CT |
|---|---|---|---|---|---|---|---|---|---|---|---|
| 1 | Fund | Attribute | Start Date | End Date | 10-day Multiplier | 50-day Multiplier | | | | | |
| 2 | IWC | Close | 12/31/2008 | 12/31/2018 | 18.18% | 3.92% | | | | | |
| 3 | | | | | | | Algorithm Signal | | | In&Out Return Cal | |
| 4 | Date | Close | Short SMA | Long SMA | Short EMA | Long EMA | In/Out Position | Signal | Transaction Price | Daily Return | 1+ Daily Return |
| 71 | 4/7/2009 | 27.14 | 27.28 | 26.38 | 27.17 | 27.24 | -0.07 | | | | |
| 72 | 4/8/2009 | 27.74 | 27.39 | 26.36 | 27.27 | 27.26 | 0.01 | | | | |
| 73 | 4/9/2009 | 29.16 | 27.77 | 26.37 | 27.61 | 27.33 | 0.28 | Buy | $28.49 | 2.35% | 102.35% |
| 74 | 4/13/2009 | 29.28 | 28.14 | 26.36 | 27.92 | 27.41 | 0.51 | | | CS73 2.35% | 100.41% |
| 75 | 4/14/2009 | 28.46 | 28.32 | 26.35 | 28.02 | 27.45 | 0.56 | | | | |
| 76 | 4/15/2009 | 29.03 | 28.42 | 26.37 | 28.20 | 27.51 | 0.69 | | | | |
| 77 | 4/16/2009 | 29.82 | 28.58 | 26.39 | 28.49 | 27.60 | 0.89 | | | | |
| 78 | 4/17/2009 | 30.16 | 28.85 | 26.41 | 28.80 | 27.70 | 1.09 | | | | |
| 79 | 4/20/2009 | 28.55 | 29.03 | 26.41 | 28.75 | 27.74 | 1.01 | | | [illegible] | [illegible] |
| 80 | 4/21/2009 | 29.68 | 29.27 | 26.43 | 28.92 | 27.81 | 1.11 | | | 3.96% | 103.96% |
| 81 | 4/22/2009 | 29.7 | 29.34 | 26.43 | 29.06 | 27.89 | 1.17 | | | 0.07% | 100.07% |
| 82 | 4/23/2009 | 29.4 | 29.35 | 26.43 | 29.12 | 27.96 | 1.18 | | | -1.01% | 98.99% |

```
=if(CQ74="Sell",(CK73-
CK72)/CK72,if(CQ73="Sell",(CR73-
CK72)/CK72, if(or(CP73<0,CP73="
",CQ74="Buy")," ",if(CQ73="Buy",
(CK73-CR73)/CR73,(CK73-
CK72)/CK72))))
```

Figure 4 illustrates the formula used in column CS to identify when the strategy should be in position, based on the signals illustrated in columns CP through CR, and thus when to list daily

As illustrated by **Figure 5**, daily returns are summated to determine cumulative return. Column CU illustrates the cumulative return of the strategy.

**Figure 5.** Calculating cumulative returns

`fx =product($CT$69:CT76)-1`

| | CP | CQ | CR | CS | CT | CU | CV |
|---|---|---|---|---|---|---|---|
| 1 | | | | | | | |
| 2 | | | | | | | |
| 3 | Algorithm Signal | | | In&Out Return Calculations | | | Buy |
| 4 | In/Out Position | Signal | Transaction Price | Daily Return | 1+ Daily Return | CU76 1.90% × ive Return | Daily Return B&H |
| 72 | 0.01 | | | | | `=product($CT$69:CT76)-1` | 2.21% |
| 73 | 0.28 | Buy | $28.49 | 2.35% | 102.35% | 2.35% | 5.12% |
| 74 | 0.51 | | | 0.41% | 100.41% | 2.77% | 0.41% |
| 75 | 0.56 | | | -2.80% | 97.20% | -0.11% | -2.80% |
| 76 | 0.69 | | | 2.00% | 102.00% | 1.90% | 2.00% |
| 77 | 0.89 | | | 2.72% | 102.72% | 4.67% | 2.72% |
| 78 | 1.09 | | | 1.14% | 101.14% | 5.86% | 1.14% |
| 79 | 1.01 | | | -5.34% | 94.66% | 0.21% | -5.34% |

Figure 5 illustrates how cumulative return is calculated. Column CT adds 1 to the daily returns presented in column CS, and then column CU summates the daily returns, and subtracts out 1.

**Figure 6** displays the return calculations for the three strategies employed throughout the study. Demonstrated in blue is the conventional buy and hold strategy. Demonstrated in red is the moving average crossover strategy. Demonstrated in yellow is a version of the moving average crossover strategy that invests in a proxy for risk free securities when out of the market. The model allows the user to choose the annual risk-free rate. From there, the algorithm determines the daily periodic rate to solve for the daily returns of the strategy when invested in the risk-free proxy.

**Figure 6.** Risk free proxy for In&In strategy

`fx =if(CT217=" ",(1+$CZ$2)^(1)-1," ")+1`

| | CS | CT | CU | CV | CW | CX | CY | CZ |
|---|---|---|---|---|---|---|---|---|
| 1 | | | | | | | Ann. Risk Free Rate | Daily Periodic Rate |
| 2 | | | | | | | 1.37% | 0.0037% |
| 3 | In&Out Return Calculations | | | Buy&Hold Return Calculations | | | | In&In Return Calculations |
| 4 | Daily Return | 1+ Daily Return | In&Out Cumulative Return | Daily Return B&H | 1+Daily Return B&H | B&H Cumulative Return | Daily Return Risk Free | 1+Daily Return In&In |
| 215 | 2.04% | 102.04% | 29.80% | 2.04% | 102.04% | 43.50% | #VALUE! | 102.04% |
| 216 | -0.35% | 99.65% | 29.34% | -3.03% | 96.97% | 39.15% | #VALUE! | 99.65% |
| 217 | | | 29.34% | -0.95% | 99.05% | 37.83% | 100.00% | 100.00% |
| 218 | | | 29.34% | 1.41% | 101.41% | 39.77% | 100.00% | 100.00% |
| 219 | | | 29.34% | -1.55% | 98.45% | 37.60% | CY217 100.00% × | 100.00% |
| 220 | | | 29.34% | 3.36% | 103.36% | 42.22% | `=if(CT217=" ",(1+$CZ$2)^(1)-1," ")+1` | [illegible] |
| 221 | | | 29.34% | 0.05% | 100.05% | 42.30% | 100.00% | 100.00% |

Figure 6 illustrates how the model uses a proxy a for the annual risk-free rate, located in cell CY2, to determine the daily periodic rate, located in cell CZ2. On days when the In&Out is out of the market, the model uses the daily periodic rate to determine the return of the In&In strategy.

## Testing Population

The development of our testing population was based on the methodology employed by Marshall et al. (2012) and Han et al. (2012). These studies illustrate the performance of trend-following trading strategies on different portfolios of stocks. While the majority of studies that precede 2012 examine either populations of stocks or large cap indices like the Dow Jones Industrial Average, both of the 2012 studies divide up the U.S. equity universe based on factors like market capitalization and return volatility, as they examine the performance of trading strategies across these portfolios of stocks. However, the studies are largely theoretical, as many of the portfolios observed in the studies are not represented by investable products.

The intention of this study is to examine the performance of a trading strategy across portfolios of stocks that are readily available to public investors, such as exchange traded funds (ETFs). Specifically, we examine a population of ETFs that track value-weighted indices that are assembled and weighted based on the market capitalization of United States companies. Our testing population includes the largest and most liquid United States core equity ETFs and includes products from the three largest ETF issuers, including BlackRock, State Street Global Advisors (SSGA), and Vanguard, as well as one ETF from Charles Schwab and one ETF from First Trust.

The ETF selection represents a variety of weighted-average market capitalizations and provides a larger sample set than those of previous empirical studies. To determine our testing population, we began by examining all the ETFs held on U.S. exchanges. We then eliminated all asset classes aside from equity and all equity ETFs with exposure to companies not held on U.S. exchanges. We then eliminated all style ETFs, such as growth

and value ETFs, as well as all the ETFs that factor in additional considerations in their construction, such as high dividend payout ratios, low beta, momentum, etc. From this list, we then eliminated all ETFs that had weighting schemes other than value-weighted, including those that are equal-weighted or price-weighted, such as DIA, the SPDR Dow Jones Industrial Average ETF.

We then narrowed this list to the most efficient and liquid ETFs in each asset class, by using the ETF.com efficiency, tradability, and fit scoring systems. The ETF.com Efficiency Score illustrates how well a fund delivers on its promises in areas such as cost, index tracking, and associated risks. This composite score evaluates a fund on factors such as expense ratios, goodness of fit to benchmark, tracking difference, and a breadth of risk measurements from structural risks to tax risks and fund closure risks. The ETF.com Tradability Score illustrates the level of expense and uncertainty that an investor might encounter when buying or selling a fund in the open market. In doing so, it accounts for on-screen liquidity at retail levels as well as block liquidity at institutional levels and considers both fund level metrics and those of the underlying holdings.

The study acknowledges that choosing the most efficient ETFs works counter to the intention of the study. For example, more efficiently traded ETFs means less information asymmetry, which, proposed by the hypothesis, should reduce the return potential of the algorithm. However, this allows the study to control for factors that may incorporate additional noise into the results. More specifically, choosing the most efficient ETFs eliminates return differences that stem from drastic differences in the efficiency and tradability of the portfolios.

Our final screen eliminated ETFs that did not have 10 years of price data in Google Finance, whether it was because the funds were launched after 12/31/2008 or because Google Sheets does not carry their full price histories. **Table** 1 illustrates our ETF testing population.

**Table 1.** Testing population

| | Ticker | Asset Class | Issuer | Wtd. Avg. Mkt. Cap (B) | Efficiency | Tradability | Fit |
|---|---|---|---|---|---|---|---|
| 1 | OEF | Equity: U.S. - Mega Cap | BlackRock | 321.12 | 97 | 100 | 93 |
| 2 | MGC | Equity: U.S. - Mega Cap | Vanguard | 250.71 | 98 | 100 | 99 |
| 3 | SPY | Equity: U.S. - Large Cap | SSGA | 218.16 | 99 | 99 | 97 |
| 4 | IWB | Equity: U.S. - Large Cap | BlackRock | 197 | 98 | 99 | 94 |
| 5 | IYY | Equity: U.S. - Large Cap | BlackRock | 191.69 | 97 | 96 | 98 |
| 6 | IWV | Equity: U.S. - Total Market | BlackRock | 183.96 | 97 | 99 | 99 |
| 7 | ITOT | Equity: U.S. - Total Market | BlackRock | 182.52 | 100 | 98 | 99 |
| 8 | VTI | Equity: U.S. - Total Market | Vanguard | 182.5 | 99 | 100 | 99 |
| 9 | VO | Equity: U.S. - Mid Cap | Vanguard | 16.2 | 98 | 99 | 95 |
| 10 | IWR | Equity: U.S. - Mid Cap | BlackRock | 15.63 | 97 | 98 | 92 |
| 11 | JKG | Equity: U.S. - Mid Cap | BlackRock | 14.4 | 93 | 94 | 86 |
| 12 | SCHM | Equity: U.S. - Mid Cap | Charles Schwab | 8.18 | 100 | 99 | 89 |
| 13 | IJH | Equity: U.S. - Mid Cap | BlackRock | 5.65 | 100 | 99 | 82 |
| 14 | MDY | Equity: U.S. - Mid Cap | SSGA | 5.488 | 95 | 98 | 82 |
| 15 | JKJ | Equity: U.S. - Small Cap | BlackRock | 3.27 | 97 | 73 | 80 |
| 16 | IWM | Equity: U.S. - Small Cap | BlackRock | 2.45 | 98 | 98 | 86 |
| 17 | IJR | Equity: U.S. - Small Cap | BlackRock | 1.92 | 100 | 98 | 81 |
| 18 | SLY | Equity: U.S. - Small Cap | SSGA | 1.91 | 98 | 96 | 82 |
| 19 | FDM | Equity: U.S. - Micro Cap | First Trust | 0.68034 | 87 | 70 | 59 |
| 20 | IWC | Equity: U.S. - Micro Cap | BlackRock | 0.671 | 85 | 89 | 80 |

Table 1 illustrates the testing population used in this study. It is a population of 20 exchange traded funds (ETFs). Also presented in the table include the asset class of the ETF, the issuer, the weighted average market capitalization, and the efficiency, tradability, and fit scores as defined by ETF.com.

## Testing Period

The ETF was invented by State Street Global Advisors in 1993 with the launch of the SPDR S&P 500 ETF. Due to this fact, the available testing period is limited to the relatively short history of this type of investment product. For example, all of the ETFs examined in this study were launched between 1993 and 2008. Part of the reason we chose

the period from December 31, 2008 to December 31, 2018 was because we wanted to observe at least a 10-year period that would include all of the selected ETFs.

Within the 10-year period, we also examined the 5-year, 3-year, and 1-year lookback periods ending on December 31, 2018. We use these periods as the basis for our performance analysis, because investment research analysts most often employ these periods when evaluating the performance of fund managers. While 1-year and 3-year performance suggests a fund manager’s more recent performance, the 5-year and 10-year periods are considered to be better measures of an investment manager’s longer-term performance.

Finally, we wanted to observe a period that had both up and down markets, so we could observe how the strategy performs in both situations. This study is conducted over a 10-year sample period starting December 31, 2008, immediately following the financial crisis of 2007 and 2008. This is an intriguing period to examine, as the algorithm is predetermined to underperform, as illustrated by Hutchinson and O’Brien (2014). In fact, Hutchinson and O’Brien indicate that in periods following financial crises, the average returns of trend following strategies are less than half of those in no-crisis periods.

Further, in the first twenty-four months following the start of a crisis, trend following strategies produce nearly one third of the return earned in no-crisis periods. Therefore, while one could question whether the study period was cherry picked to artificially improve the outcome for tested algorithm, we would argue just the opposite; the starting date of December 31, 2018 is more likely to have had a negative impact on the algorithm’s performance.

Selected Variables

In the preceding section, we explained how returns are calculated. Now, we will explain the other variables used in our analysis. The first is volatility, which we calculate by using the standard deviation of daily returns across the strategies examined.

$$STDEV_{daily} = \sqrt{\sum \frac{(return_i - return_{average})^2}{n-1}}$$

We then annualized the standard deviation for comparison across different annual time periods. All annualization calculations used in this study assume 250 trading days per year.

$$STDEV_{annual} = \sqrt{\sum \frac{(return_i - return_{average})^2}{n-1}} * \sqrt{250}$$

**Figure 7** illustrates the how the model calculates annual standard deviation.

**Figure 7.** Calculating standard deviation

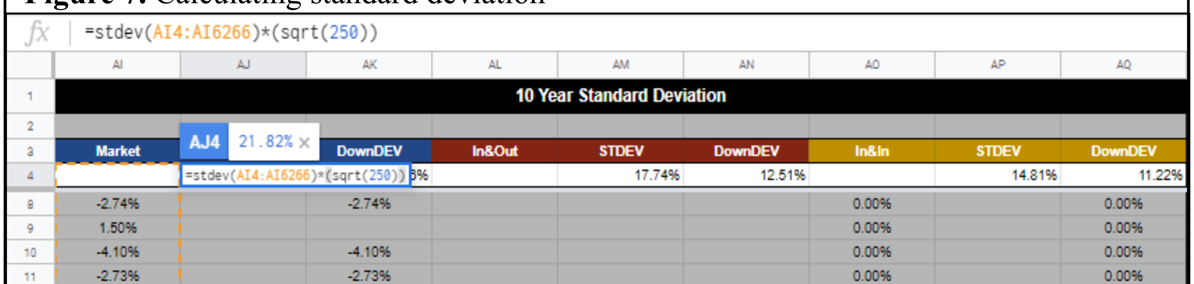


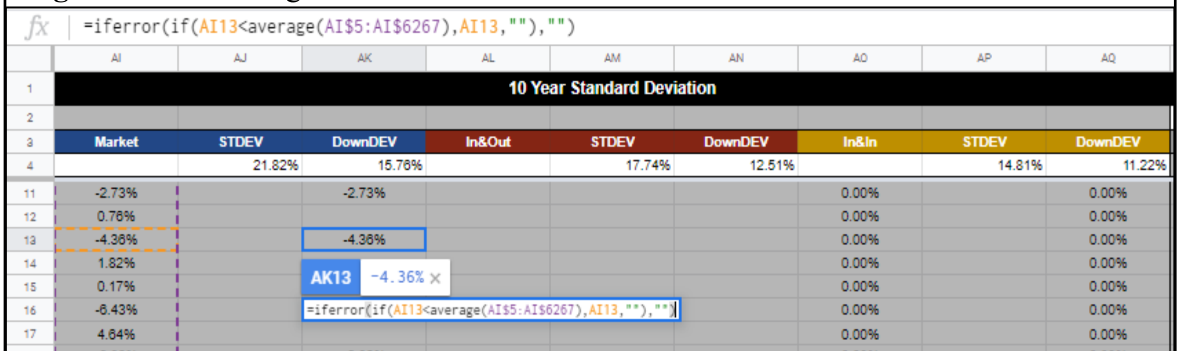

Figure 7 illustrates how the model calculates annual standard deviation of returns. For the Buy&Hold strategy, daily returns are illustrated in column AI. In cell AJ4, the STDEV function is used to determine the standard deviation, coupled with an annualization factor.

As risk-averse investors are primarily concerned with limiting their downside risk, the next variable we examined was downside deviation. Downside deviation is a measure of downside risk that only considers the returns that are below the arithmetic mean.

$$DownDEV_{daily} = \sqrt{\sum \frac{(return_i - return_{average})^2 \ where \ r_i < r_{average}}{n-1}}$$

Below, **Figure 8** depicts how the model calculates downside deviation. Column AK displays only the daily returns that are below the arithmetic mean.

**Figure 8.** Calculating deviations below the mean


=iferror(if(AI13<average(AI$5:AI$6267),AI13,""),"")

| | AI | AJ | AK | AL | AM | AN | AO | AP | AQ |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 10 Year Standard Deviation | | | | | | | | |
| 2 | | | | | | | | | |
| 3 | Market | STDEV | DownDEV | In&Out | STDEV | DownDEV | In&In | STDEV | DownDEV |
| 4 | | 21.82% | 15.76% | | 17.74% | 12.51% | | 14.81% | 11.22% |
| 11 | -2.73% | | -2.73% | | | | 0.00% | | 0.00% |
| 12 | 0.76% | | | | | | 0.00% | | 0.00% |
| 13 | -4.36% | | -4.36% | | | | 0.00% | | 0.00% |
| 14 | 1.82% | | | | | | 0.00% | | 0.00% |
| 15 | 0.17% | | | | | | 0.00% | | 0.00% |
| 16 | -6.43% | | | | | | 0.00% | | 0.00% |
| 17 | 4.64% | | | | | | 0.00% | | 0.00% |

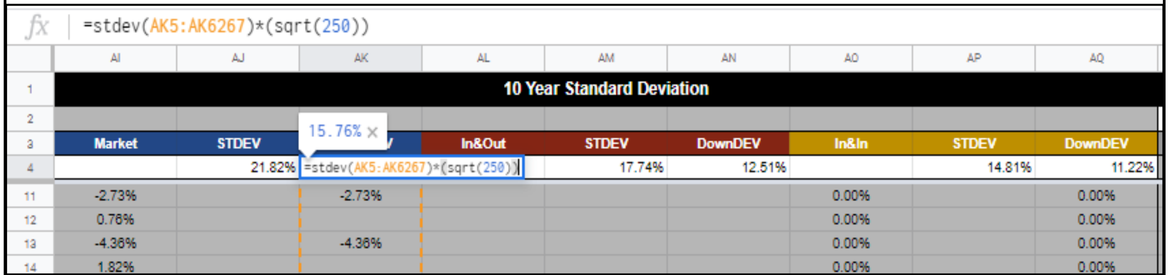


Figure 8 illustrates how the model calculates downside return deviations. For the Buy&Hold strategy, daily returns are illustrated in column AI. Then, the model displays the return deviations that are below the arithmetic mean return in column AK.

Illustrated in **Figure 9** below, Cell AK4 finds the annualized downside deviation through finding the standard deviation of the daily returns that are below the arithmetic mean.

$$DownDEV_{annual} = \sqrt{\sum \frac{(return_i - return_{average})^2 where \ r_i < r_{average}}{n-1}} * \sqrt{250}$$

**Figure 9.** Calculating annual downside deviation



fx =stdev(AK5:AK6267)*(sqrt(250))

| | AI | AJ | AK | AL | AM | AN | AO | AP | AQ |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 10 Year Standard Deviation | | | | | | | | |
| 2 | | | 15.76% × | | | | | | |
| 3 | Market | STDEV | V | In&Out | STDEV | DownDEV | In&In | STDEV | DownDEV |
| 4 | | 21.82% | =stdev(AK5:AK6267)*(sqrt(250)) | | 17.74% | 12.51% | | 14.81% | 11.22% |
| 11 | -2.73% | | -2.73% | | | | 0.00% | | 0.00% |
| 12 | 0.76% | | | | | | 0.00% | | 0.00% |
| 13 | -4.36% | | -4.36% | | | | 0.00% | | 0.00% |
| 14 | 1.82% | | | | | | 0.00% | | 0.00% |

Figure 9 illustrates how the model calculates annual downside deviation. Similar to how standard deviation was calculated, cell AK4 identifies the standard deviation of daily returns below the mean, and multiplies by the annualization factor.

Annual standard deviation of returns was then divided by annual return to solve for coefficient of variation.

$$Coefficient\ of\ Variation\ (CV) = \left(\frac{STDEV_{annual}}{Return_{annual}}\right)$$

The coefficient of variation represents the ratio of the standard deviation to the mean return, measuring the dispersion of data points in a data series around the mean. Specifically, in finance, the coefficient of variation provides investors with an idea of how much risk is assumed in comparison to the amount of expected return. If the coefficient of variation is lower, it indicates a better risk-return trade-off. **Figure 11** illustrates how the model calculates coefficient of variation.

**Figure 10.** Calculating coefficient of variation (CV)

=D8/D7

| | Ticker | Class | Brand | | Provider | | Description | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | IWC | | | | | | | | | | | |
| | 10 Year Return | | | 5 Year Return | | | 3 Year Return | | | 1 Year Return | | |
| | Buy&Hold | In&Out | In&In | Buy&Hold | In&Out | In&In | Buy&Hold | In&Out | In&In | Buy&Hold | In&Out | In&In |
| Cumulative Return | 156.67% | 107.22% | 113.17% | 8.99% | -0.91% | 0.57% | 12.05% | 15.21% | 16.07% | -14.59% | 1.62% | 1.95% |
| Annualized Return | 9.88% | 7.56% | 7.86% | 1.74% | -0.18% | 0.11% | 3.86% | 4.83% | 5.09% | -14.59% | 1.62% | 1.95% |
| Standard Deviation | 21.82% | 17.74% | 14.81% | 16.85% | 14.65% | 12.08% | 16.41% | 13.70% | 11.73% | 17.34% | 12.62% | 10.16% |
| Downside Deviation | D10 2.21 | 12.51% | 11.22% | 11.67% | 10.50% | 10.47% | 11.63% | 9.75% | 9.06% | 12.70% | 9.69% | 8.38% |
| Coeff. of Variation | =D8/D7 | 2.35 | 1.88 | 9.71 | -79.87 | 105.32 | 4.25 | 2.84 | 2.30 | -1.19 | 7.77 | 5.20 |

Figure 10 illustrates how the model calculates coefficient of variation (CV). In row 10, CV is found through dividing the standard deviation of returns found in row 8, by annual return found in row 7.

Due to the amount of time it requires to run the algorithm, each ETF was tested one at a time. We copied the data from each test and pasted it into a list on the "EMAC_Population Summary" sheet. We tested the population in order by weighted average market capitalization from greatest to least, and all tables and charts are ordered by this descriptive variable. **Figure 11** displays a portion of the outputs generated by the model.

**Figure 11.** Model output

fx IWC

| | A | B | C | D | E | F | G | H | I | J | K | L |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 175 | | 18 | SLY | Equity: U.S. - Small Cap | SSGA | 1.91 | 98 | 96 | 82 | | | |
| 176 | | | 10 Year Return | | | 5 Year Return | | | 3 Year Return | | | |
| 177 | | | Buy&Hold | In&Out | In&In | Buy&Hold | In&Out | In&In | Buy&Hold | In&Out | In&In | Buy&Hol |
| 178 | | Cumulative Return | 216.00% | 95.42% | 100.68% | 16.12% | 4.95% | 6.56% | 18.99% | 20.65% | 21.57% | -10.29% |
| 179 | | Annualized Return | 12.19% | 6.93% | 7.21% | 3.03% | 0.97% | 1.28% | 5.97% | 6.46% | 6.73% | -10.29% |
| 180 | | Standard Deviation | 20.84% | 17.67% | 14.93% | 15.98% | 13.89% | 11.38% | 16.05% | 13.84% | 11.80% | 17.59% |
| 181 | | Downside Deviation | 15.13% | 12.49% | 11.26% | 11.25% | 9.69% | 8.77% | 11.49% | 9.85% | 9.04% | 13.35% |
| 182 | | Coeff. of Variation | 170.94% | 254.93% | 207.01% | 526.90% | 1430.85% | 889.44% | 269.01% | 214.30% | 175.36% | -170.97 |
| 183 | | | | | | | | | | | | |
| 184 | | | Ticker | Asset Class | Issuer | Wtd. Avg. Mkt. Cap (B) | | | | | | |
| 185 | | 19 | FDM | Equity: U.S. - Micro Cap | First Trust | 0.68034 | 87 | 70 | 59 | | | |
| 186 | | | 10 Year Return | | | 5 Year Return | | | 3 Year Return | | | |
| 187 | | | Buy&Hold | In&Out | In&In | Buy&Hold | In&Out | In&In | Buy&Hold | In&Out | In&In | Buy&Hol |
| 188 | | Cumulative Return | 172.19% | 60.57% | 65.05% | 24.48% | 2.66% | 4.17% | 20.62% | 13.04% | 13.93% | -14.82% |
| 189 | | Annualized Return | 10.53% | 4.85% | 5.14% | 4.48% | 0.53% | 0.82% | 6.45% | 4.17% | 4.44% | -14.82% |
| 190 | | Standard Deviation | 23.06% | 19.59% | 16.41% | 15.47% | 14.18% | 11.74% | 15.07% | 13.17% | 11.14% | 14.48% |
| 191 | | Downside Deviation | 16.94% | 13.96% | 12.27% | 10.39% | 9.56% | 8.75% | 10.20% | 8.92% | 8.18% | 10.42% |
| 192 | | Coeff. of Variation | 218.93% | 403.90% | 319.29% | 345.59% | 2691.98% | 1432.43% | 233.75% | 315.90% | 250.81% | -97.72% |
| 193 | | | | | | | | | | | | |
| 194 | | | Ticker | Asset Class | Issuer | Wtd. Avg. Mkt. Cap (B) | | | | | | |
| 195 | | 20 | IWC | Equity: U.S. - Micro Cap | BlackRock | 0.671 | 85 | 89 | 80 | | | |
| 196 | | | 10 Year Return | | | 5 Year Return | | | 3 Year Return | | | |
| 197 | | | Buy&Hold | In&Out | In&In | Buy&Hold | In&Out | In&In | Buy&Hold | In&Out | In&In | Buy&Hol |
| 198 | | Cumulative Return | 156.67% | 107.22% | 113.17% | 8.99% | -0.91% | 0.57% | 12.05% | 15.21% | 16.07% | -14.59% |
| 199 | | Annualized Return | 9.88% | 7.56% | 7.86% | 1.74% | -0.18% | 0.11% | 3.86% | 4.83% | 5.09% | -14.59% |
| 200 | | Standard Deviation | 21.82% | 17.74% | 14.81% | 16.85% | 14.65% | 12.08% | 16.41% | 13.70% | 11.73% | 17.34% |
| 201 | | Downside Deviation | 15.76% | 12.51% | 11.22% | 11.67% | 10.50% | 10.47% | 11.63% | 9.75% | 9.06% | 12.70% |
| 202 | | Coeff. of Variation | 220.72% | 234.75% | 188.40% | 970.76% | -7986.86% | 10531.52% | 424.66% | 283.62% | 230.35% | -118.86 |

Figure 11 illustrates how the individual outputs of the model are listed by security. All variables over all time periods are listed in each output. The model then reformats the data in a variety of ways to generate visual representations of the data by variable.

From here, the model reformats the data in a variety of ways, so it may generate visual representations of the data including charts and tables. The tables examined throughout the Results portion are based on a number of tables found in Han et al. (2012). However, this study does not observe Sharpe ratio, Fama and French three-factor alpha, or capital asset pricing model (CAPM) alpha. We also do not calculate Jensen's alpha as Marshall et al. (2012) does. Instead, the four variables that we consider include average returns, standard deviation, downside deviation, and coefficient of variation.

# CHAPTER 5

# RESULTS

In this section, the study illustrates the performance of the moving average strategy in comparison with the conventional buy and hold strategy. For simplicity, the study refers to the conventional buy and hold strategy as the Buy&Hold strategy. Likewise, it refers to the moving average crossover strategy as the In&Out strategy. This section begins with an examination of the Buy&Hold strategy across four time periods. The periods examined include a 10-year, 5-year, 3-year and 1-year period all ending December 31, 2018. Observing different length periods with a common end date allows the study to observe the impact of the 2018 market selloff on periods leading up to the selloff. The study's analysis then shifts to examine all 1-year periods within the 10-year period so it may examine the multiple hypotheses proposed.

The four periods have a common end date, meaning they all experience the fourth quarter selloff of 2018. In this case, the longer periods have more exposure to the post-crisis bull market, and thus the impact of the 2018 selloff is smaller. The shorter, more recent periods have relatively more exposure to the 2018 selloff, so the impact of the selloff is relatively larger. This allows the study to examine the influence of the selloff on strategies that begin at different times.

In 2018, the stock market did poorly, which means the Buy&Hold strategy did poorly. During this time, the In&Out strategy consistently outperformed the Buy&Hold strategy across ETFs. In fact, the outperformance relative to the Buy&Hold strategy was greatest

on the ETFs that performed the worst during the period. This is because the trading algorithm exited the positions relatively more effectively on the ETFs that went on to experience the largest selloffs. In the 1-year period, the smaller cap ETFs experienced the most dramatic selloffs. In fact, the smaller the weighted average market capitalization of the ETF, the worse was the performance of the Buy&Hold strategy, and thus the better was the relative performance of the In&Out strategy. The objective of this study is to answer the question *why?* More specifically, the study tries to determine the relationship between the relative performance of the In&Out strategy and variables like annual return, standard deviation, and downside deviation of the Buy&Hold strategy. The study is primarily motivated by the tendency of the trading algorithm to outperform during market selloffs, and thus examines factors that may be driving the relative performance of the algorithm.

Throughout the first part of the Results section, the study examines the performance of the Buy&Hold strategy and illustrates the impact of the selloff on all four periods. Then, the study examines the performance of the In&Out strategy and the impact of the 2018 selloff on annual returns. Next, the study examines the performance of the In&Out strategy relative to the Buy&Hold strategy, and illustrates the effect of the 2018 selloff on the relative performance throughout the different time periods.

Later in this section, the study examines the individual, 1-year periods within the 10-year window as to draw conclusions with a greater level of statistical significance. In this section, the study also includes 2008 to incorporate an additional down market period to the sample. In doing so, the study uses a variety of statistical tests to draw conclusions about each hypothesis individually. Within the Hypothesis Testing subsection, the study uses difference of mean tests (t-tests) to examine its first-level hypotheses and linear

regressions to examine its second-level hypotheses. The t-tests allow the study to conclude with significance that the trading strategy underperforms the Buy&Hold strategy over a 1-year period, on average. Although it underperforms over a 1-year period on average, the trading algorithm consistently reduces both the standard deviation and the downside deviation of the underlying investment. In periods where there are sharp selloffs, the In&Out strategy's ability to reduce the impact of the selloff leads to outperformance. The linear regression tests allow the study to conclude with statistical significance that the relative performance of the In&Out strategy is correlated not only with the annual return of the Buy&Hold strategy, but also with the standard deviation and downside deviation of the Buy&Hold strategy as well.

## Buy&Hold Strategy Analysis

This section begins with a high-level examination of the Buy&Hold strategy, followed by subsections that examine the variables individually. In this section, a series of illustrations help visually display the data observed throughout the course of the study. The tables below are sorted by weighted average market capitalization and color-coordinated based on asset class. Within each testing period, the study examines four variables: annualized return, standard deviation, downside deviation and coefficient of variation over the four testing periods and across all ETFs. Below each table is a list of statistical measures to provide further information about each variable. **Table 2** illustrates the results of the Buy&Hold strategy over the 10-year, 5-year, 3-year and 1-year periods.

**Table 2.** Buy&Hold Strategy Analysis

| Buy&Hold Strategy Analysis | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Testing Pop. | 10 Year | | | | 5 Year | | | | 3 Year | | | | 1 Year | | | |
| Symbol | Ann. Ret. | STDEV | DownDEV | CV | Ann. Ret. | STDEV | DownDEV | CV | Ann. Ret. | STDEV | DownDEV | CV | Ann. Ret. | STDEV | DownDEV | CV |
| OEF | 9.84% | 15.94% | 12.43% | 161.87% | 6.13% | 13.39% | 10.65% | 218.27% | 6.24% | 13.23% | 11.15% | 212.01% | -6.88% | 17.88% | 14.81% | -259.94% |
| MGC | 10.57% | 16.13% | 12.67% | 152.66% | 6.47% | 13.11% | 10.48% | 202.50% | 6.87% | 12.97% | 10.89% | 188.73% | -6.26% | 17.31% | 14.41% | -276.25% |
| SPY | 10.63% | 16.44% | 12.85% | 154.70% | 6.15% | 13.20% | 10.52% | 214.67% | 6.36% | 13.00% | 10.84% | 204.54% | -7.16% | 17.05% | 13.97% | -238.06% |
| IWB | 10.88% | 16.55% | 12.99% | 152.03% | 5.98% | 13.23% | 10.59% | 221.05% | 6.29% | 13.08% | 11.00% | 207.95% | -7.60% | 17.00% | 14.08% | -223.52% |
| IYY | 10.83% | 16.65% | 13.04% | 153.72% | 5.81% | 13.18% | 10.41% | 226.68% | 6.15% | 13.07% | 10.84% | 212.44% | -7.72% | 16.92% | 13.85% | -219.30% |
| IWV | 10.84% | 16.91% | 13.20% | 155.90% | 5.71% | 13.33% | 10.57% | 233.35% | 6.23% | 13.20% | 11.00% | 211.87% | -7.96% | 16.93% | 13.95% | -212.71% |
| ITOT | 10.76% | 16.67% | 13.01% | 154.97% | 5.95% | 13.26% | 10.54% | 222.86% | 6.26% | 13.13% | 10.95% | 209.86% | -8.05% | 16.89% | 13.95% | -209.90% |
| VTI | 10.95% | 16.78% | 13.12% | 153.28% | 5.76% | 13.27% | 10.57% | 230.51% | 6.28% | 13.11% | 10.95% | 208.77% | -7.88% | 16.83% | 13.95% | -213.45% |
| VB | 12.21% | 18.81% | 14.54% | 154.02% | 4.55% | 13.85% | 10.81% | 304.08% | 4.21% | 13.65% | 10.99% | 323.95% | -11.63% | 16.31% | 12.96% | -140.28% |
| VO | 11.92% | 18.23% | 14.06% | 152.90% | 4.28% | 13.52% | 10.44% | 315.74% | 4.50% | 13.46% | 10.74% | 298.93% | -11.49% | 16.03% | 12.75% | -139.46% |
| IWR | 12.36% | 18.40% | 14.35% | 148.79% | 4.42% | 13.34% | 10.33% | 301.42% | 3.53% | 13.14% | 10.66% | 372.40% | -13.71% | 15.69% | 12.74% | -114.37% |
| JKG | 6.55% | 16.30% | 12.74% | 248.65% | 4.91% | 13.78% | 10.50% | 280.48% | 5.57% | 13.73% | 10.77% | 246.49% | -10.93% | 16.26% | 12.79% | -148.81% |
| IJH | 11.91% | 19.01% | 14.31% | 159.64% | 4.24% | 14.08% | 10.49% | 332.13% | 5.28% | 14.25% | 10.89% | 269.84% | -13.42% | 16.20% | 12.87% | -120.74% |
| MDY | 11.91% | 19.09% | 14.33% | 160.25% | 4.24% | 14.13% | 10.52% | 333.43% | 5.25% | 14.22% | 10.78% | 270.56% | -13.33% | 16.16% | 12.70% | -121.19% |
| JKJ | 11.91% | 19.09% | 14.33% | 160.25% | 4.24% | 14.13% | 10.52% | 333.43% | 5.25% | 14.22% | 10.78% | 270.56% | -13.33% | 16.16% | 12.70% | -121.19% |
| IWM | 10.44% | 21.51% | 15.68% | 206.10% | 2.91% | 16.27% | 11.64% | 558.40% | 5.22% | 16.27% | 12.10% | 311.57% | -12.86% | 17.97% | 14.00% | -139.80% |
| IJR | 12.10% | 20.85% | 15.01% | 172.38% | 4.78% | 15.85% | 11.05% | 331.53% | 7.29% | 16.17% | 11.55% | 221.92% | -10.30% | 17.80% | 13.74% | -172.84% |
| SLY | 12.19% | 20.84% | 15.13% | 170.94% | 3.03% | 15.98% | 11.25% | 526.90% | 5.97% | 16.05% | 11.49% | 269.01% | -10.29% | 17.59% | 13.35% | -170.97% |
| FDM | 10.53% | 23.06% | 16.94% | 218.93% | 4.48% | 15.47% | 10.39% | 345.59% | 6.45% | 15.07% | 10.20% | 233.75% | -14.82% | 14.48% | 10.42% | -97.72% |
| IWC | 9.88% | 21.82% | 15.76% | 220.72% | 1.74% | 16.85% | 11.67% | 970.76% | 3.86% | 16.41% | 11.63% | 424.66% | -14.59% | 17.34% | 12.70% | -118.86% |
| Mean | 10.96% | 18.45% | 14.02% | 170.63% | 4.79% | 14.16% | 10.70% | 335.19% | 5.65% | 14.07% | 11.01% | 258.49% | -10.51% | 16.74% | 13.34% | -172.97% |
| Median | 10.86% | 18.31% | 14.19% | 157.77% | 4.67% | 13.65% | 10.53% | 302.75% | 6.06% | 13.56% | 10.92% | 240.12% | -10.61% | 16.91% | 13.55% | -159.89% |
| Min | 6.55% | 15.94% | 12.43% | 148.79% | 1.74% | 13.11% | 10.33% | 202.50% | 3.53% | 12.97% | 10.20% | 188.73% | -14.82% | 14.48% | 10.42% | -276.25% |
| Max | 12.36% | 23.06% | 16.94% | 248.65% | 6.47% | 16.85% | 11.67% | 970.76% | 7.29% | 16.41% | 12.10% | 424.66% | -6.26% | 17.97% | 14.81% | -97.72% |

Table 2 illustrates the performance of the Buy&Hold strategy across the ETF population, over the selected time periods. Within each time period, the table illustrates the annual return, standard deviation, downside deviation, and CV of each ETF. The statistical variables at the bottom allow for further interpretation.

Following the Financial Crisis of 2007-2008**,** the mean annual return of the testing population over the 10-year period ending December 31, 2018 was 10.96%. Despite the long bull market, in December of 2018, the SPDR S&P 500 ETF (SPY) fell 14.87% from its 52-week high in late September of 2018. On average, the testing population experienced an annual loss of 10.51% in 2018. Over the 10-year period, the large cap and total market ETFs performed the best on average, followed by the mega cap ETFs, small cap ETFs and micro cap ETFs. The mid cap ETFs performed the worst during this period. Similar to the 10-year period, the larger capitalization ETFs outperform the smaller capitalization ETFs

on average throughout the 5-year period. With the exception of the micro cap ETFs, the smaller cap ETFs outperform the larger cap ETFs in the 3-year period, while the smaller cap ETFs consistently outperform the larger cap ETFs in the 1-year period. We will examine each of these variables individually in the following sections.

<u>Buy&Hold Annual Returns</u>

Within the following charts, the ETFs are organized by weighted average market capitalization, with OEF, the iShares Mega Cap ETF on the far left, and IWC, the iShares Micro Cap ETF on the far right. The ETFs are color-coordinated based on their asset class. For example, the mega cap ETFs are illustrated in red, the large cap ETFs are illustrated in green, the total market ETFs are illustrated in yellow, the mid cap ETFs are illustrated in blue, the small cap ETFs are illustrated in purple, and the micro cap ETFs are illustrated in pink

**Chart 2** illustrates the annual returns of the Buy&Hold strategy across the ETFs, over the four testing periods. Over the 10-year, 5-year, and 3-year periods, all of the ETFs had positive returns. Over the most recent 1-year period, however, all of the ETFs had negative returns, with large cap ETFs outperforming small cap ETFs.

**Chart 2.** Buy&Hold Annual Return

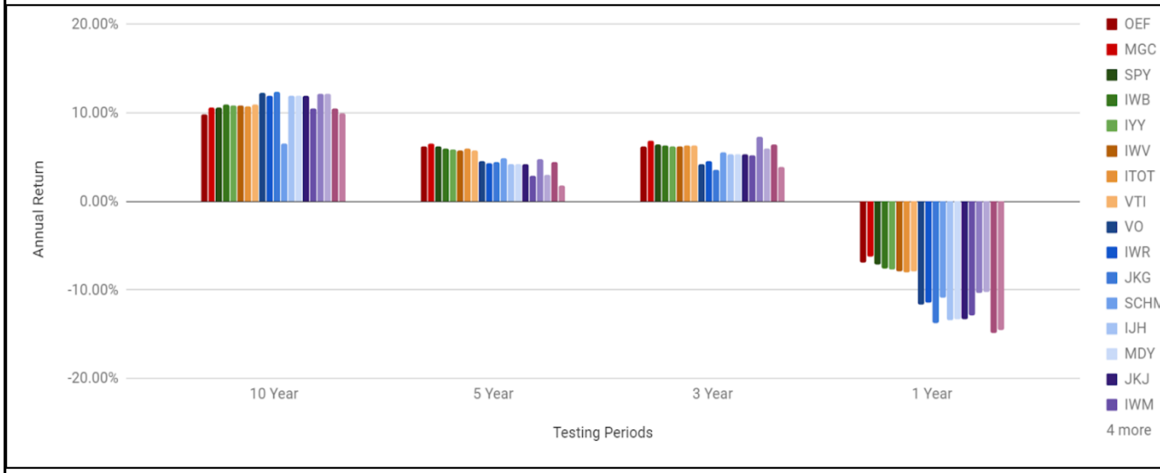



Chart 2 illustrates the annual returns of the Buy&Hold strategy across the ETF population, over the selected time periods.

This is primarily due to the late fourth quarter selloff that occurred in 2018. All four testing periods have exposure to the selloff as they all end in December 31st, 2018. In the shorter and more recent time periods, the impact of the selloff on the performance of the Buy&Hold strategy was more significant, where the smaller, more volatile ETFs such as FDM and IWC performed the worst. Conversely, OEF and MGC, the largest ETFs by market cap, performed the best during the 1-year period. Despite the fact that the smaller cap ETFs experienced a worse selloff in 2018 than the larger cap ETFs, the smaller cap ETFs still managed to outperform the larger cap ETFs in the 10-year period, due to their momentous growth throughout the period. However, in the shorter, more recent periods, the heightened selloffs of the smaller cap ETFs relative to the larger cap ETFs caused the smaller cap ETFs to underperform the larger cap ETFs in the 5-year and 3-year periods.

Buy&Hold Standard Deviation

Here, we examine the level of volatility through looking at the standard deviation of returns of the Buy&Hold strategy. **Chart 3** illustrates the standard deviation of the

Buy&Hold strategy across the ETFs being tested. As expected, the small cap ETFs were generally more volatile than the large cap ETFs, over the 10-year period. In fact, over all periods, the small cap ETFs were the most volatile**.** Over all periods aside from the 1-year period, the mega cap ETFs were the least volatile. The return volatility during the 5-year and 3-year periods was very comparable across ETFs, with the smaller cap ETFs exceeding the volatility of the larger cap ETFs on average. The ETFs were consistently more volatile during the 1-year period than they were during the 5-year and 3-year periods.

**Chart 3.** Buy&Hold Standard Deviation

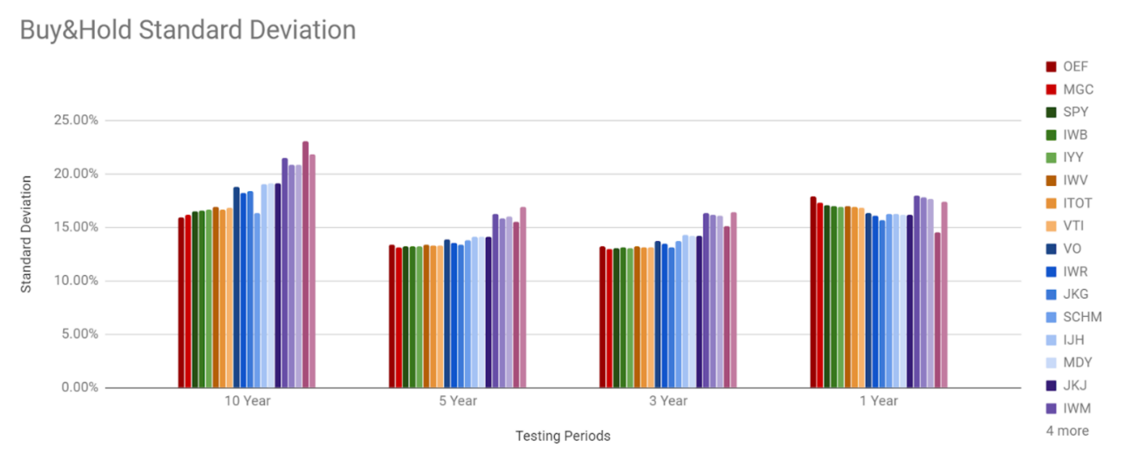



Chart 3 illustrates the standard deviation of the Buy&Hold strategy across the ETF population, over the selected time periods.

<u>Buy&Hold Downside Deviation</u>

As long-only investors are not generally concerned about the upside volatility of their investments, the study compares the level of downside deviation of the Buy&Hold strategy. **Chart 4** displays the downside deviation of the Buy&Hold strategy over the selected time periods. During the 10-year period, the small and micro cap ETFs had the highest level of downside deviation where the large cap ETFs had the lowest. During the 5-year and 3-year periods, the level of downside deviation was relatively consistent across

ETFs, with the exception of the small cap ETFs. In the 1-year period, the ETFs experienced a higher level of downside deviation compared to the 5-year and 3-year periods. In the same period, mega cap ETFs had the highest level of downside deviation, where the mid cap ETFs generally had the lowest. It is interesting to note that the larger cap ETFs had more downside deviation in the 1-year period than they did throughout the 10-year period.

**Chart 4.** Buy&Hold Downside Deviation

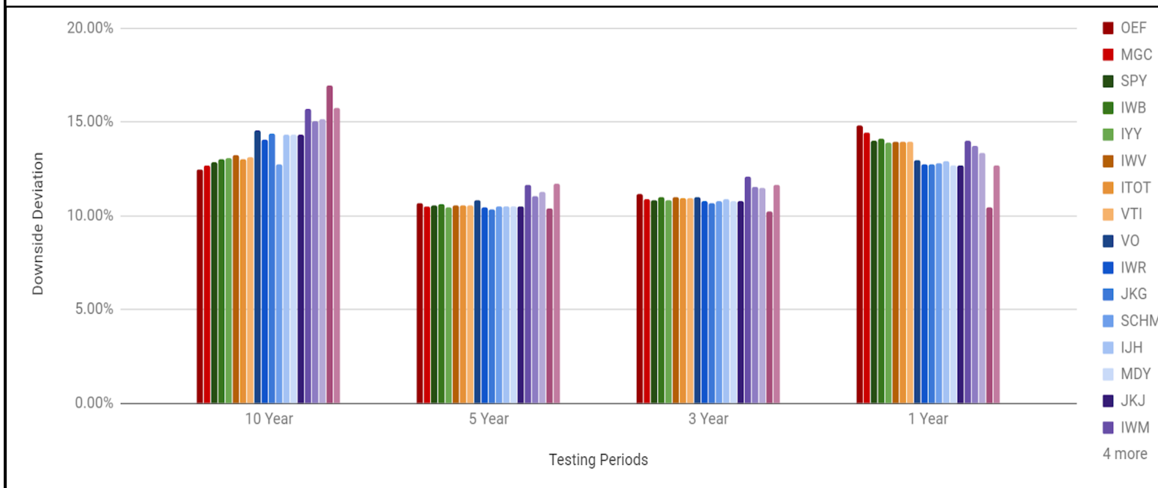



Chart 4 illustrates the downside deviation of the Buy&Hold strategy across the ETF population, over the selected time periods.

<u>Buy&Hold Coefficient of Variation</u>

**Chart 5** illustrates the coefficient of variation of the Buy&Hold strategy across our ETF population. If the coefficient of variation is lower, it indicates a better risk-return trade-off. As illustrated by the charts below, over the 10-year, 5-year, and 3-year periods, the large cap ETFs generally had a better risk-return trade-off, as defined by the coefficient of variation. Note, however, that a negative CV can result when returns are negative. Thus, a negative CV shouldn't necessarily be interpreted as "low" and therefore a better risk-return tradeoff. A negative CV can be difficult to interpret. In one sense, when observing

a negative CV, a less negative CV would imply a better risk-return trade off due to lower losses.

Illustrated by the chart, the larger cap ETFs consistently had a lower CV, and thus a better risk-return tradeoff throughout the 10-year, 5-year, and 3-year periods. Displayed in **Chart 2** and **Chart 3** the smaller ETFs underperformed the larger ETFs in the 3-year and 5-year periods and experienced a higher level of standard deviation in both periods. These observations are reflected in the CV ratio, below. In the 5-year period, the smaller ETFs achieved their returns by assuming a higher amount of risk, and thus the risk-return tradeoffs, as demonstrated by the CV ratio, were higher.

**Chart 5.** Buy&Hold Coefficient of Variation (CV)

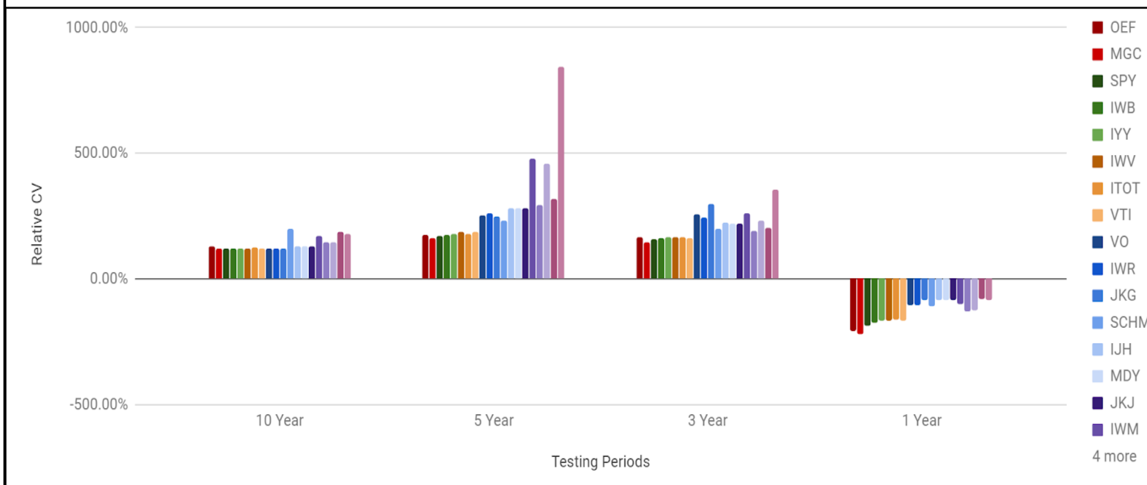



Chart 5 illustrates the CV of the Buy&Hold strategy across the ETF population, over the selected time periods.

## In&Out Strategy Analysis

Here, the study examines the In&Out strategy in the same format as it did the Buy&Hold strategy. First, the study presents the data gathered during the observed periods, across the selected variables. The tables below are sorted by weighted average market

capitalization, which is found in the second column. Within each testing period, the study examines four variables: annualized return, standard deviation, downside deviation and coefficient of variation over the four testing periods and across all ETFs. Below each table is a list of statistical variables to better illustrate the data sets. **Table 3** illustrates the results of the In&Out strategy over the 10-year, 5-year, 3-year and 1-year periods.

**Table 3.** In&Out Strategy Analysis

| In&Out Strategy Analysis | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Testing Pop. | 10 Year | | | | 5 Year | | | | 3 Year | | | | 1 Year | | | |
| Symbol | Ann. Ret. | STDEV | DownDEV | CV | Ann. Ret. | STDEV | DownDEV | CV | Ann. Ret. | STDEV | DownDEV | CV | Ann. Ret. | STDEV | DownDEV | CV |
| OEF | 5.94% | 12.49% | 9.74% | 210.24% | 3.03% | 10.69% | 8.96% | 8.96% | 5.34% | 10.27% | 9.66% | 9.66% | -5.52% | 14.20% | 14.62% | 14.62% |
| MGC | 6.76% | 12.58% | 9.70% | 186.15% | 1.78% | 10.53% | 8.82% | 8.82% | 5.52% | 10.08% | 9.36% | 9.36% | -3.10% | 13.71% | 14.29% | 14.29% |
| SPY | 6.86% | 12.71% | 9.92% | 185.13% | 2.27% | 10.51% | 8.88% | 8.88% | 6.53% | 10.09% | 9.41% | 9.41% | -3.75% | 13.51% | 13.79% | 13.79% |
| IWB | 8.69% | 12.93% | 10.13% | 148.82% | 2.85% | 10.46% | 8.83% | 8.83% | 6.47% | 10.15% | 9.52% | 9.52% | -4.42% | 13.21% | 13.90% | 13.90% |
| IYY | 7.78% | 12.99% | 10.06% | 167.00% | 1.85% | 10.43% | 8.62% | 8.62% | 5.55% | 10.09% | 9.28% | 9.28% | -6.59% | 12.93% | 13.50% | 13.50% |
| IWV | 8.04% | 13.22% | 10.26% | 164.50% | 1.25% | 10.66% | 8.91% | 8.91% | 4.27% | 10.34% | 9.67% | 9.67% | -7.74% | 13.17% | 13.65% | 13.65% |
| ITOT | 7.50% | 13.19% | 10.12% | 175.88% | 1.55% | 10.64% | 8.91% | 8.91% | 5.29% | 10.33% | 9.60% | 9.60% | -6.66% | 13.22% | 13.74% | 13.74% |
| VTI | 7.55% | 13.11% | 10.17% | 173.73% | 1.28% | 10.61% | 8.88% | 8.88% | 4.71% | 10.25% | 9.54% | 9.54% | -6.68% | 13.13% | 13.82% | 13.82% |
| VO | 6.30% | 14.97% | 11.42% | 237.47% | 0.99% | 11.38% | 9.25% | 9.25% | 4.86% | 10.75% | 9.31% | 9.31% | -5.75% | 12.20% | 11.40% | 11.40% |
| IWR | 7.14% | 14.57% | 11.01% | 204.04% | 2.34% | 11.21% | 8.87% | 8.87% | 6.54% | 10.95% | 9.22% | 9.22% | -4.34% | 12.13% | 11.39% | 11.39% |
| JKG | 8.02% | 14.80% | 11.25% | 184.45% | 3.10% | 10.93% | 8.65% | 8.65% | 5.77% | 10.55% | 9.16% | 9.16% | -6.02% | 11.90% | 11.52% | 11.52% |
| SCHM | 1.99% | 12.89% | 9.74% | 646.08% | 2.06% | 11.40% | 8.88% | 8.88% | 7.12% | 11.06% | 8.99% | 8.99% | -4.77% | 12.01% | 10.89% | 10.89% |
| IJH | 6.56% | 15.28% | 11.21% | 233.15% | 2.57% | 11.97% | 9.01% | 9.01% | 6.22% | 11.71% | 9.15% | 9.15% | -4.00% | 11.42% | 10.15% | 10.15% |
| MDY | 5.60% | 15.31% | 11.24% | 273.36% | 2.34% | 11.90% | 8.93% | 8.93% | 5.93% | 11.57% | 8.98% | 8.98% | -4.05% | 11.20% | 9.79% | 9.79% |
| JKJ | 5.60% | 15.31% | 11.24% | 273.36% | 2.34% | 11.90% | 8.93% | 8.93% | 5.93% | 11.57% | 8.98% | 8.98% | -4.05% | 11.20% | 9.79% | 9.79% |
| IWM | 4.63% | 17.51% | 12.49% | 377.90% | 1.05% | 13.96% | 10.17% | 10.17% | 7.26% | 13.64% | 10.15% | 10.15% | 1.29% | 12.86% | 10.77% | 10.77% |
| IJR | 7.96% | 17.39% | 11.97% | 218.48% | 2.85% | 14.07% | 9.63% | 9.63% | 7.77% | 13.97% | 9.85% | 9.85% | 2.18% | 13.41% | 10.72% | 10.72% |
| SLY | 6.93% | 17.67% | 12.49% | 254.93% | 0.97% | 13.89% | 9.69% | 9.69% | 6.46% | 13.84% | 9.85% | 9.85% | 4.43% | 12.97% | 10.34% | 10.34% |
| FDM | 4.85% | 19.59% | 13.96% | 403.90% | 0.53% | 14.18% | 9.56% | 9.56% | 4.17% | 13.17% | 8.92% | 8.92% | -2.21% | 11.74% | 9.05% | 9.05% |
| IWC | 7.56% | 17.74% | 12.51% | 234.75% | -0.18% | 14.65% | 10.50% | 10.50% | 4.83% | 13.70% | 9.75% | 9.75% | 1.62% | 12.62% | 9.69% | 9.69% |
| Mean | 6.61% | 14.81% | 11.03% | 247.67% | 1.84% | 11.80% | 9.14% | 9.14% | 5.83% | 11.40% | 9.42% | 9.42% | -3.51% | 12.64% | 11.84% | 11.84% |
| Median | 6.90% | 14.68% | 11.11% | 214.36% | 1.96% | 11.30% | 8.92% | 8.92% | 5.85% | 10.85% | 9.38% | 9.38% | -4.20% | 12.89% | 11.39% | 11.39% |
| Min | 1.99% | 12.49% | 9.70% | 148.82% | -0.18% | 10.43% | 8.62% | 8.62% | 4.17% | 10.08% | 8.92% | 8.92% | -7.74% | 11.20% | 9.05% | 9.05% |
| Max | 8.69% | 19.59% | 13.96% | 646.08% | 3.10% | 14.65% | 10.50% | 10.50% | 7.77% | 13.97% | 10.15% | 10.15% | 4.43% | 14.20% | 14.62% | 14.62% |

Table 3 illustrates the performance of the In&Out strategy across the ETF population, over the selected time periods. Within each period, the table illustrates the annual return, standard deviation, downside deviation, and CV of each ETF. The statistical variables at the bottom allow for further interpretation.

Following the Financial Crisis of 2007-2008**,** the mean annual return of the In&Out strategy across the testing population over the 10-year period ending December 31, 2018,

was 6.61%. In terms of annual return, the In&Out strategy underperformed the Buy&Hold strategy significantly during this period. However, in the 1-year period, the testing population experienced an annual loss of only 3.51% compared with the 10.51% loss exhibited by the Buy&Hold strategy on average.

Similar to the Buy&Hold strategy, over the 10-year period, the large cap and total market ETFs performed the best on average, followed by the mega cap ETFs, small cap ETFs and micro cap ETFs. The mid cap ETFs performed the worst during this period. Throughout the 5-year and 3-year periods, the performance of the In&Out strategy across the testing population was more varied. In the 5-year period, the mega caps performed the best, followed by the large caps, mid caps, small caps and total market ETFs. The micro cap ETFs performed the worst. In the 3-year period, the small cap ETFs performed the best, followed by the large caps, the mid caps, and the mega cap ETFs. The total market and micro cap ETFs performed the worst.

In&Out Annual Returns

**Chart 6** illustrates the In&Out performance across the ETFs being tested. Similar to the Buy&Hold strategy, the In&Out strategy exhibited positive returns in the 10-year, 5-year, and 3-year periods. Whereas the Buy&Hold strategy exhibited negative returns across all ETFs in the 1-year period, the In&Out exhibited positive returns with the following ETFs: IWM, IJR, SLY and IWC. The listed ETFs represent four of the five smallest ETFs in the sample.

**Chart 6.** In&Out Annual Return

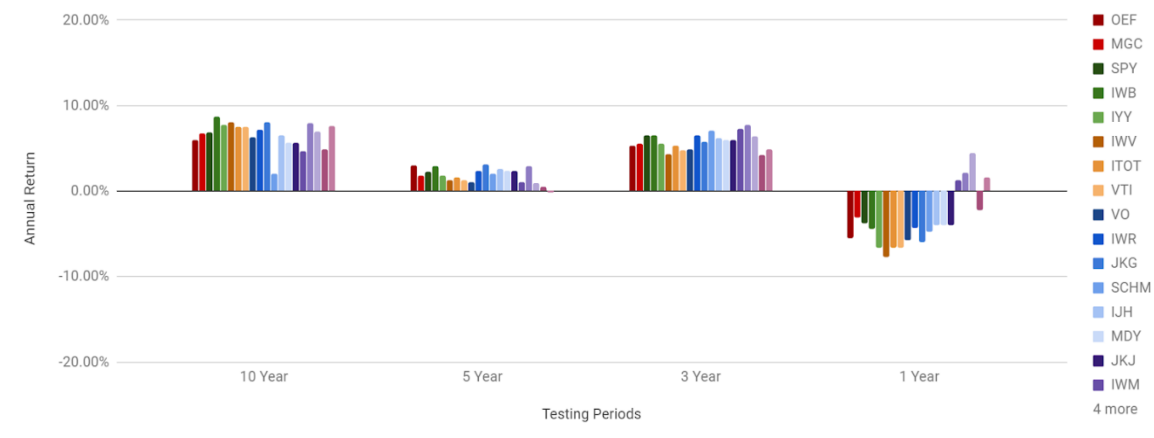



Chart 6 illustrates the annual returns of the In&Out strategy across the ETF population, over the selected time periods.

<u>In&Out Standard Deviation</u>

**Chart 7** illustrates the standard deviation of the In&Out strategy across the ETFs being tested. Similar to the Buy&Hold strategy, the small cap ETFs are generally more volatile than the large cap ETFs, especially as the time frame gets longer. During the 3-year period, the mid cap, small cap and micro cap ETFs experienced a standard deviation of 11.10%, 13.25% and 13.44% respectively on average. During the same time period, the mega cap, large cap, and total market ETFs experienced a standard deviation of 10.18%, 10.11%, and 10.0% respectively on average. This illustrates that the algorithm was more volatile across smaller ETFs during this period. This relationship is nearly constant throughout the 5-year period, and further exaggerated during the 10-year period, with smaller cap ETFs far exceeding the standard deviation of larger cap ETFs.

**Chart 7.** In&Out Standard Deviation

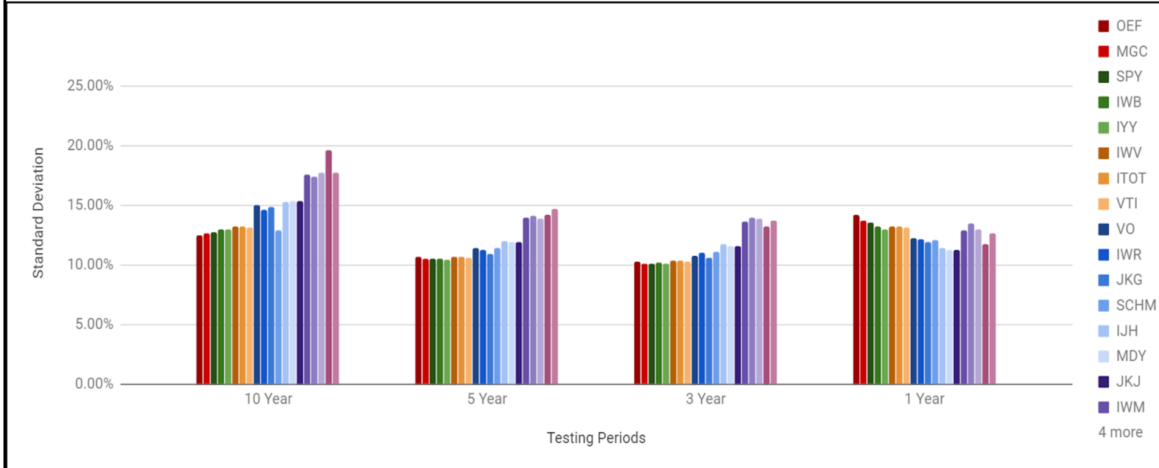



Chart 7 illustrates the standard deviation of the In&Out strategy across the ETF population, over the selected time periods.

<u>In&Out Downside Deviation</u>

**Chart 8** illustrates the downside deviation of the In&Out strategy over the selected time periods. Similar to the Buy&Hold strategy, during the 10-year period, the small and micro cap ETFs had the highest level of downside deviation, whereas the large cap ETFs had the lowest. During the 5-year and 3-year periods, the level of downside deviation was relatively consistent across ETFs. In the 1-year period, mega cap ETFs had the highest level of downside deviation, where the mid cap ETFs generally had the lowest. This makes sense as the algorithm was able to reduce the downside deviation the most on the ETFs with the sharpest selloffs.

**Chart 8.** In&Out Downside Deviation

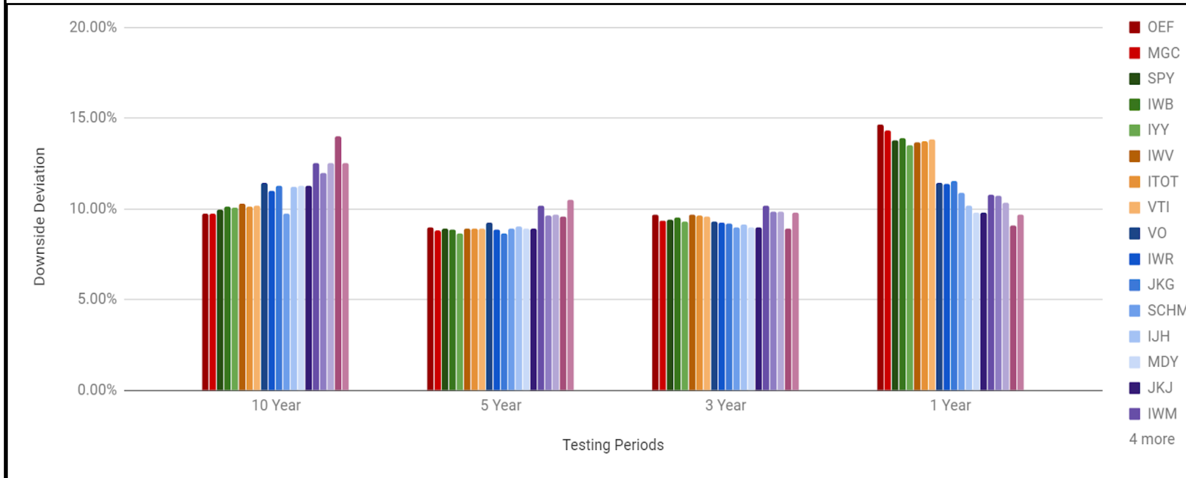



Chart 8 illustrates the downside deviation of the In&Out strategy across the ETF population, over the selected time periods.

<u>In&Out Coefficient of Variation (CV)</u>

**Chart 9** illustrates the coefficient of variation of the In&Out strategy across ETFs over the selected time periods.

**Chart 9.** In&Out Coefficient of Variation (CV)

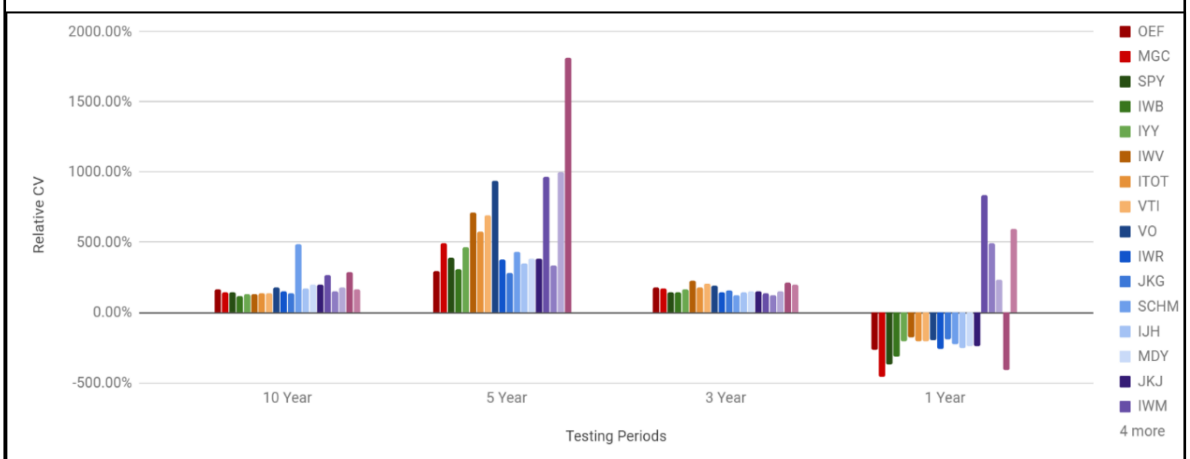



Chart 9 illustrates the CV of the In&Out strategy across the ETF population, over the selected time periods.

As the Buy&Hold strategy exhibited negative returns across all ETFs over the 1-year period, the Buy&Hold CV across ETFs in the 1-year period was negative. However,

as the In&Out strategy exhibited positive returns across the majority of small cap ETFs in the 1-year period, it also exhibited a positive CV in those situations. Although the algorithm was not consistently positive throughout the ETFs over the 1-year period, the CV of the strategy was consistently less negative than that of the Buy&Hold strategy in the 1-year period. We will further examine the comparative performance between the In&Out strategy and the Buy&Hold strategy in the next section.

## Relative Performance Analysis

Here, the study examines the level of performance of the In&Out strategy relative to the Buy&Hold strategy. In the table below, the positive (negative) values listed in the annual return columns indicate that the In&Out strategy on the corresponding ETF outperformed the Buy&Hold strategy. Similarly, the values listed in the standard deviation (STDEV) and downside deviation columns (DownDEV) are adjusted to present information the same way. In other words, positive integers represent an outperformance in terms of the corresponding variable. For example, with OEF, the In&Out achieved a relative standard deviation of 3.45%, which means that the In&Out strategy experienced 3.45% less standard deviation than that of the Buy&Hold strategy. Illustrated by the table, the In&Out strategy reduced the volatility and downside volatility compared to the Buy&Hold strategy across all situations.

Conversely, the negative (positive) values listed in the coefficient of variation (CV) column suggest that the In&Out strategy decreased (increased) the CV with the corresponding ETF, which indicates a better (worse) risk-return trade-off. For example, in the case of the iShares Mega Cap ETF (OEF), the Buy&Hold strategy achieved 9.84% average return over the 10-year period, while the In&Out strategy achieved an average

return of 5.94% over the same period. As illustrated by **Table 6**, the algorithm achieved 3.91% less annual returns than that of the Buy&Hold strategy over the 10-year period. Additionally, the In&Out strategy reduced the standard deviation of returns of the Buy&Hold strategy by 3.45%, while reducing the downside deviation of the portfolio by 2.70%, and effectively improving the coefficient of variation of the Buy&Hold by 48.38%. In fact, although the algorithm underperformed the Buy&Hold strategy across all ETFs over the 10-year period, the In&Out strategy achieved its returns at a lower risk-return tradeoff then the Buy&Hold strategy as demonstrated by a lower CV ratio. Because the CV ratio of the In&Out strategy was lower across all ETFs over the 10-year period, the relative CV ratio is negative.

Similar to the 10-year period, in the 1-year period, the relative CV ratio across the ETF population was negative, meaning the In&Out strategy achieved its returns through assuming a lower amount of risk than the Buy&Hold strategy. This is especially relevant as the values in the annual return column during the 10-year are positive across the ETF population. Not only did the In&Out strategy outperform the Buy&Hold strategy across all ETFs during the 1-year period, it also achieved its returns at a lower level of risk, on average.

**Table 4.** In&Out Relative Analysis

| Relative Analysis | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Testing Pop. | 10 Year | | | | 5 Year | | | | 3 Year | | | | 1 Year | | | |
| Symbol | Ann. Ret. | STDEV | DownDEV | CV | Ann. Ret. | STDEV | DownDEV | CV | Ann. Ret. | STDEV | DownDEV | CV | Ann. Ret. | STDEV | DownDEV | CV |
| OEF | -3.91% | 3.45% | 2.70% | -48.38% | -3.10% | 2.69% | 1.69% | 209.31% | -0.90% | 2.96% | 1.49% | 202.35% | 1.36% | 3.68% | 0.18% | -274.56% |
| MGC | -3.81% | 3.55% | 2.97% | -33.50% | -4.69% | 2.58% | 1.67% | 193.68% | -1.35% | 2.89% | 1.54% | 179.37% | 3.16% | 3.60% | 0.12% | -290.54% |
| SPY | -3.76% | 3.73% | 2.93% | -30.43% | -3.88% | 2.70% | 1.64% | 205.79% | 0.17% | 2.92% | 1.43% | 195.14% | 3.42% | 3.53% | 0.18% | -251.85% |
| IWB | -2.19% | 3.61% | 2.87% | 3.21% | -3.14% | 2.77% | 1.76% | 212.22% | 0.18% | 2.93% | 1.48% | 198.43% | 3.18% | 3.78% | 0.18% | -237.42% |
| IYY | -3.06% | 3.67% | 2.98% | -13.28% | -3.96% | 2.75% | 1.80% | 218.07% | -0.60% | 2.98% | 1.56% | 203.16% | 1.12% | 4.00% | 0.36% | -232.79% |
| IWV | -2.81% | 3.69% | 2.94% | -8.59% | -4.46% | 2.66% | 1.66% | 224.44% | -1.96% | 2.86% | 1.33% | 202.20% | 0.22% | 3.76% | 0.30% | -226.36% |
| ITOT | -3.26% | 3.48% | 2.89% | -20.91% | -4.40% | 2.62% | 1.63% | 213.95% | -0.97% | 2.81% | 1.35% | 200.26% | 1.39% | 3.67% | 0.21% | -223.64% |
| VTI | -3.40% | 3.67% | 2.95% | -20.44% | -4.47% | 2.66% | 1.69% | 221.63% | -1.56% | 2.86% | 1.41% | 199.23% | 1.20% | 3.70% | 0.14% | -227.27% |
| VO | -5.91% | 3.84% | 3.12% | -83.45% | -3.56% | 2.46% | 1.56% | 294.83% | 0.65% | 2.91% | 1.69% | 314.65% | 5.88% | 4.11% | 1.56% | -151.68% |
| IWR | -4.78% | 3.66% | 3.06% | -51.14% | -1.94% | 2.31% | 1.57% | 306.87% | 2.04% | 2.51% | 1.52% | 289.71% | 7.15% | 3.90% | 1.37% | -150.85% |
| JKG | -4.34% | 3.60% | 3.10% | -35.66% | -1.32% | 2.40% | 1.69% | 292.78% | 2.24% | 2.59% | 1.50% | 363.24% | 7.70% | 3.79% | 1.22% | -125.89% |
| SCHM | -4.56% | 3.41% | 2.99% | -397.43% | -2.85% | 2.38% | 1.62% | 271.59% | 1.55% | 2.67% | 1.79% | 237.50% | 6.15% | 4.25% | 1.90% | -159.70% |
| IJH | -5.35% | 3.73% | 3.10% | -73.52% | -1.67% | 2.12% | 1.48% | 323.12% | 0.94% | 2.55% | 1.74% | 260.69% | 9.43% | 4.78% | 2.72% | -130.89% |
| MDY | -6.31% | 3.78% | 3.10% | -113.11% | -1.90% | 2.23% | 1.58% | 324.50% | 0.67% | 2.65% | 1.80% | 261.58% | 9.28% | 4.96% | 2.91% | -130.98% |
| JKJ | -6.31% | 3.78% | 3.10% | -113.11% | -1.90% | 2.23% | 1.58% | 324.50% | 0.67% | 2.65% | 1.80% | 261.58% | 9.28% | 4.96% | 2.91% | -130.98% |
| IWM | -5.80% | 3.99% | 3.19% | -171.80% | -1.86% | 2.31% | 1.47% | 548.23% | 2.03% | 2.64% | 1.96% | 301.42% | 14.14% | 5.11% | 3.24% | -150.57% |
| IJR | -4.14% | 3.46% | 3.04% | -46.10% | -1.93% | 1.78% | 1.42% | 321.90% | 0.48% | 2.21% | 1.71% | 212.07% | 12.48% | 4.39% | 3.02% | -183.56% |
| SLY | -5.26% | 3.18% | 2.64% | -83.99% | -2.06% | 2.10% | 1.57% | 517.21% | 0.49% | 2.21% | 1.64% | 259.16% | 14.72% | 4.61% | 3.01% | -181.31% |
| FDM | -5.68% | 3.47% | 2.98% | -184.97% | -3.95% | 1.29% | 0.83% | 336.03% | -2.28% | 1.90% | 1.28% | 224.83% | 12.61% | 2.74% | 1.37% | -106.77% |
| IWC | -2.33% | 4.07% | 3.25% | -14.04% | -1.92% | 2.20% | 1.17% | 960.25% | 0.97% | 2.71% | 1.88% | 414.91% | 16.21% | 4.71% | 3.01% | -128.55% |
| Mean | 6.61% | 14.81% | 11.03% | 247.67% | 1.84% | 11.80% | 9.14% | 9.14% | 5.83% | 11.40% | 9.42% | 9.42% | -3.51% | 12.64% | 11.84% | 11.84% |
| Median | 6.90% | 14.68% | 11.11% | 214.36% | 1.96% | 11.30% | 8.92% | 8.92% | 5.85% | 10.85% | 9.38% | 9.38% | -4.20% | 12.89% | 11.39% | 11.39% |
| Min | 1.99% | 12.49% | 9.70% | 148.82% | -0.18% | 10.43% | 8.62% | 8.62% | 4.17% | 10.08% | 8.92% | 8.92% | -7.74% | 11.20% | 9.05% | 9.05% |
| Max | 8.69% | 19.59% | 13.96% | 646.08% | 3.10% | 14.65% | 10.50% | 10.50% | 7.77% | 13.97% | 10.15% | 10.15% | 4.43% | 14.20% | 14.62% | 14.62% |

Table 4 illustrates the performance of In&Out strategy relative to the Buy&Hold strategy across the ETF population, over the selected time periods. Within each time period, the table illustrates the annual return, standard deviation, downside deviation, and CV of each ETF. The statistical variables at the bottom allow for further interpretation.

In&Out Relative Annual Return

**Chart 10** illustrates the relative annual returns between the In&Out and the Buy&Hold strategies. If positive (negative), the In&Out strategy outperformed (underperformed) the Buy&Hold strategy on the corresponding ETF. Over the 10-year and 5-year period, the In&Out strategy consistently underperformed the Buy&Hold strategy across the testing population. However, during the 3-year period, the In&Out strategy outperformed the Buy&Hold strategy across more than half of the ETFs. Outperformance was primarily concentrated in small and mid cap ETFs. During the 1-year period, the

In&Out strategy outperformed the Buy&Hold strategy on all observed ETFs. The level of outperformance was greatest among small cap ETFs and weakest among total market ETFs.

**Chart 10.** In&Out Relative Annual Return

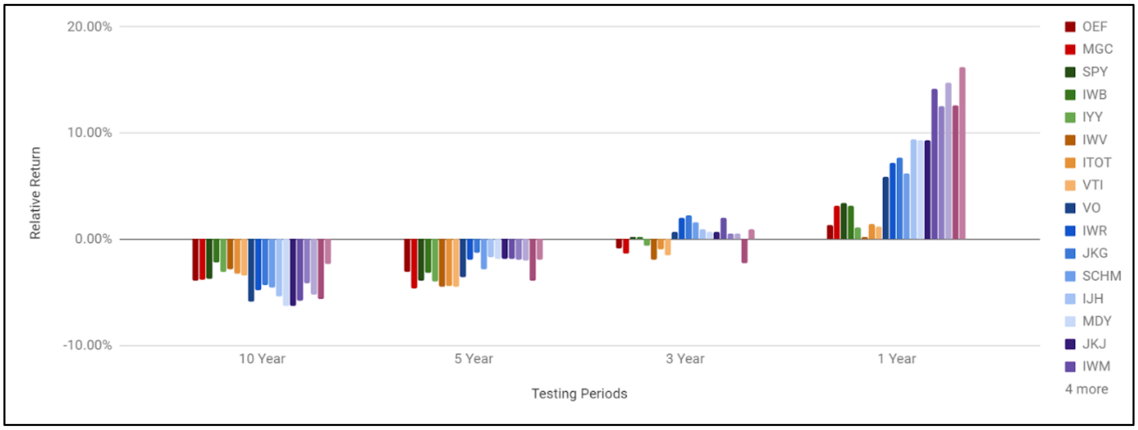



Chart 10 illustrates the annual return of the In&Out strategy relative to the annual return of the Buy&Hold strategy across the ETF population, over the selected time periods.

Illustrated by **Chart 10**, the In&Out strategy underperformed when the returns of the Buy&Hold strategy were positive. In these cases, the small cap ETFs underperformed by the greatest margin. As demonstrated by the graph, over the 10-year and 5-year periods, the In&Out strategy underperformed the Buy&Hold by a significant margin. However, during the 3-year period, the In&Out strategy outperformed the Buy&Hold strategy on more than half of the ETFs. Outperformance was most heavily concentrated among small and mid cap ETFs. During the 1-year period, the In&Out strategy outperformed the Buy&Hold strategy across all observed ETFs. The level of outperformance was greatest among small cap ETFs and weakest among total market ETFs.

In&Out Relative Standard Deviation

The study calculates relative standard deviation the same way it calculates relative return. Simply, the standard deviation of the Buy&Hold strategy is subtracted from the standard deviation of the In&Out. Illustrated in **Chart 11**, the algorithm reduced the volatility of ETFs across all ETFs over all four time periods. In the 1-year period, the algorithm reduced the standard deviation of MDY, the SPDR Mid Cap ETF, from 16.16% to 11.20%, which is a reduction of 4.96%. During the 10-year, 5-year, and 3-year periods, the algorithm reduced the volatility of large cap ETFs the most. During the 1-year period, the algorithm reduced the volatility of the small and mid cap ETFs the most.

**Chart 11.** In&Out Relative Standard Deviation

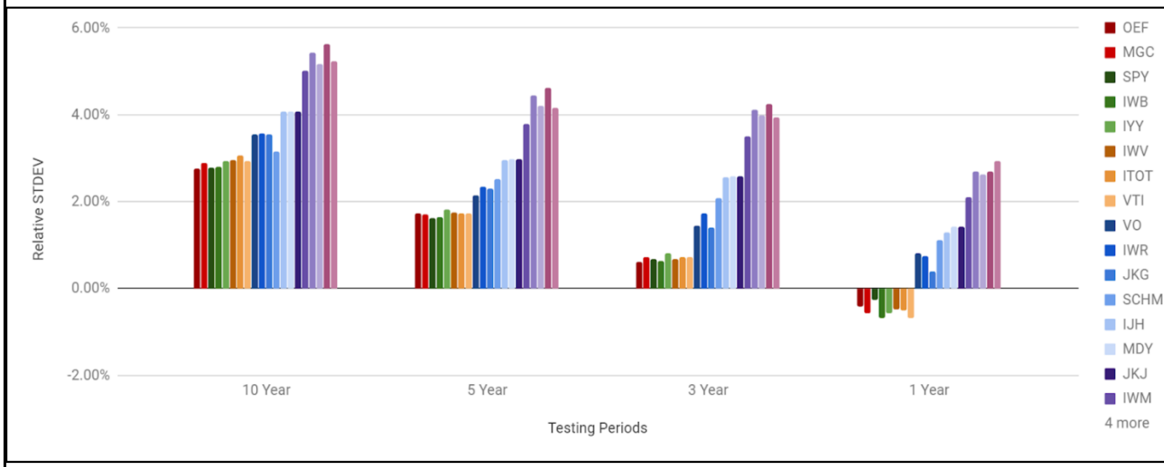



Chart 11 illustrates the standard deviation of the In&Out strategy relative to the standard deviation of the Buy&Hold strategy across the ETF population, over the selected time periods.

The In&Out strategy outperformed in terms of relative annual returns across all ETFs during the 1-year period. As illustrated by **Chart 11**, the algorithm generally has a tendency to reduce the volatility of the Buy&Hold strategy. Despite these two facts, the algorithm increased the volatility of the mega cap, large cap, and total market ETFs during the 1-year period. We further investigate this relationship in the next section.

In&Out Relative Downside Deviation

**Chart 12** illustrates the level of downside deviation of the In&Out strategy, relative to the Buy&Hold strategy. In all scenarios, the In&Out strategy reduces the downside risk of the Buy&Hold strategy. Relative to the Buy&Hold strategy over the 1-year period, the In&Out strategy eliminated more downside deviation with mid cap and small cap ETFs than it did with large cap ETFs. This was a significant driver of the In&Out strategy's outperformance during this time period.

**Chart 12.** In&Out Relative Downside Deviation

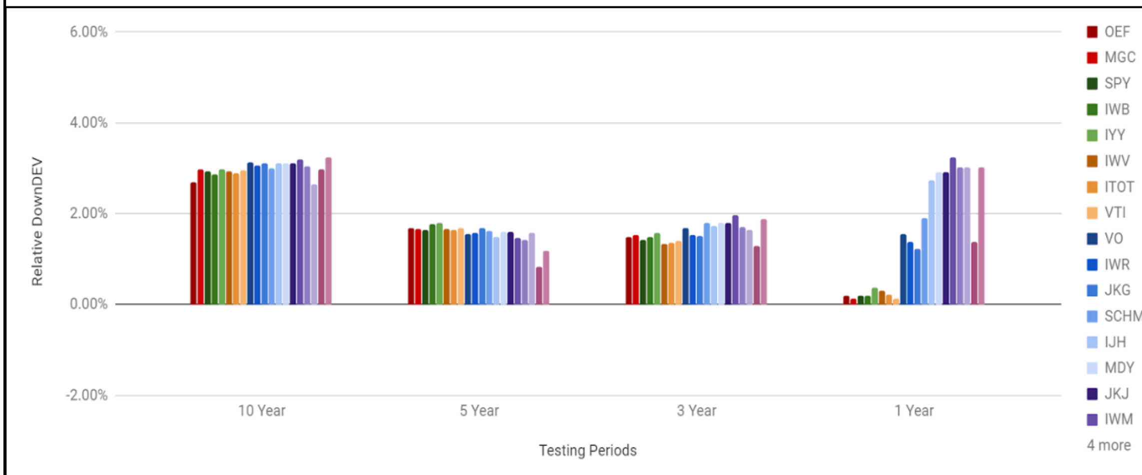



Chart 12 illustrates the downside deviation of the In&Out strategy relative to the downside deviation of the Buy&Hold strategy across the ETF population, over the selected time periods.

**Chart 11** illustrates that the algorithm exhibits a higher level of standard deviation than the Buy&Hold strategy across the mega cap, large cap, and small cap ETFs during the 1-year period. However, **Chart 12** illustrates that the algorithm experienced less downside deviation than the Buy&Hold strategy across these ETFs, meaning the algorithm managed to add upside volatility to those investments. This is an interesting observation as it is not often the case.

In&Out Relative Coefficient of Variation

**Chart 13** illustrates the coefficient of variation of the In&Out strategy relative to the coefficient of variation of the Buy&Hold strategy. If negative, the algorithm reduces the coefficient of variation, thus improving the risk-return trade-off and vic versa. Illustrated by the chart, during the 3-year and 1-year period, the algorithm reduces the coefficient of variation throughout the majority of ETFs. During the 10-year and 5-year periods, the coefficient of variation was increased by the algorithm.

**Chart 13.** Relative Coefficient of Variation (CV)

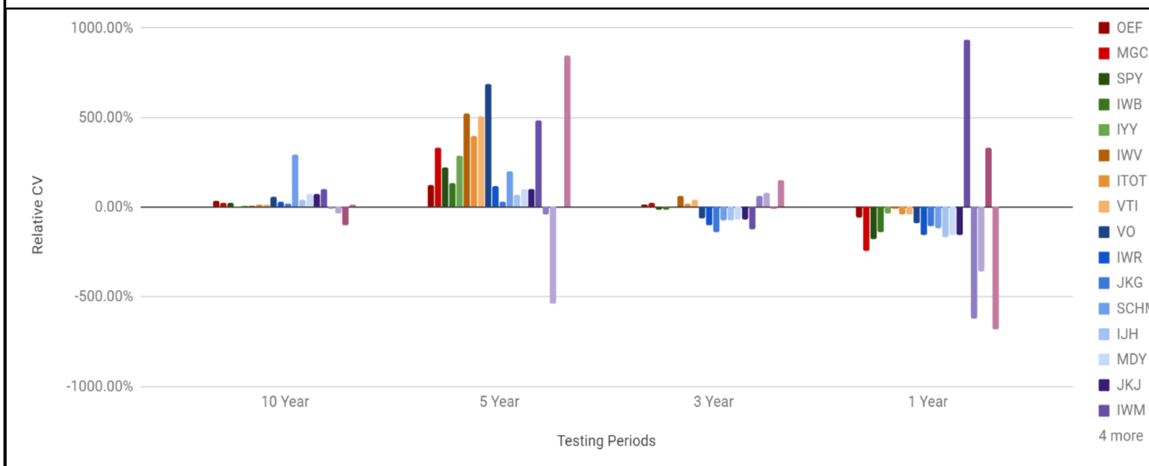



Chart 12 illustrates the downside deviation of the In&Out strategy relative to the downside deviation of the Buy&Hold strategy across the ETF population, over the selected time periods.

In&Out Relative Analysis by Asset Class

As we have an uneven number of ETFs within each category of market capitalization, we find the mean relative performance of the ETFs within each category in order to illustrate a sense of how the asset classes performed as a whole. **Table 8** is formatted the same way as previous tables, only it illustrates the mean performance of asset classes, rather than the individual performance of the ETFs.

**Table 5.** In&Out relative analysis

| In&Out Relative Analysis | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Testing Pop. | 10 Year | | | | 5 Year | | | | 3 Year | | | | 1 Year | | | |
| Asset Class | Ann. Ret. | STDEV | DownDEV | CV | Ann. Ret. | STDEV | DownDEV | CV | Ann. Ret. | STDEV | DownDEV | CV | Ann. Ret. | STDEV | DownDEV | CV |
| Mega Cap | -3.86% | 3.50% | 2.83% | -40.94% | -3.90% | 2.64% | 1.68% | 201.50% | -1.12% | 2.92% | 1.51% | 190.86% | 2.26% | 3.64% | 0.15% | -282.55% |
| Large Cap | -3.00% | 3.67% | 2.92% | -13.50% | -3.66% | 2.74% | 1.73% | 212.03% | -0.08% | 2.94% | 1.49% | 198.91% | 2.57% | 3.77% | 0.24% | -240.69% |
| Total Market | -3.16% | 3.61% | 2.92% | -16.65% | -4.45% | 2.65% | 1.66% | 220.01% | -1.50% | 2.84% | 1.36% | 200.57% | 0.94% | 3.71% | 0.22% | -225.76% |
| Mid Cap | -5.21% | 3.67% | 3.08% | -125.72% | -2.21% | 2.32% | 1.58% | 302.28% | 1.35% | 2.65% | 1.67% | 287.90% | 7.60% | 4.30% | 1.95% | -141.66% |
| Small Cap | -5.38% | 3.60% | 2.99% | -103.75% | -1.94% | 2.11% | 1.51% | 427.96% | 0.92% | 2.43% | 1.78% | 258.56% | 12.66% | 4.77% | 3.04% | -161.60% |
| Micro Cap | -4.00% | 3.77% | 3.11% | -99.50% | -2.93% | 1.75% | 1.00% | 648.14% | -0.66% | 2.31% | 1.58% | 319.87% | 14.41% | 3.73% | 2.19% | -117.66% |
| **Mean** | -4.10% | 3.64% | 2.98% | -66.68% | -3.18% | 2.37% | 1.53% | 335.32% | -0.18% | 2.68% | 1.57% | 242.78% | 6.74% | 3.98% | 1.30% | -194.99% |
| **Median** | -3.93% | 3.64% | 2.96% | -70.22% | -3.30% | 2.48% | 1.62% | 261.14% | -0.37% | 2.74% | 1.55% | 229.56% | 5.09% | 3.75% | 1.09% | -193.68% |
| **Min** | -5.38% | 3.50% | 2.83% | -125.72% | -4.45% | 1.75% | 1.00% | 201.50% | -1.50% | 2.31% | 1.36% | 190.86% | 0.94% | 3.64% | 0.15% | -282.55% |
| **Max** | -3.00% | 3.77% | 3.11% | -13.50% | -1.94% | 2.74% | 1.73% | 648.14% | 1.35% | 2.94% | 1.78% | 319.87% | 14.41% | 4.77% | 3.04% | -117.66% |

Figure 10 illustrates the performance of the In&Out strategy relative to the Buy&Hold strategy across the four variables observed. over the four selected time periods.

During the 10-year period, the In&Out strategy underperformed by varying degrees across the different market capitalization categories. The mean describes that the average relative performance between the In&Out strategy and the Buy&Hold strategy was an underperformance of 4.10%. While the mean Buy&Hold return across asset classes was 10.81%, the mean In&Out return across asset classes was 6.71%. Midcap, small cap and microcap ETFs underperformed the mean here, while large cap, mega cap, and total market ETFs outperformed the mean. The worst relative performer was the small cap population as it underperformed the Buy&Hold strategy by 5.38% on average. The best relative performer was the large cap population as it underperformed the Buy&Hold strategy by 3.00% on average.

During the 5-year period, the In&Out strategy underperformed by varying degrees across the different categories of market capitalization. The average relative performance between the In&Out strategy and the Buy&Hold strategy was an underperformance of 3.18%. While the mean Buy&Hold return across asset classes was 4.90%, the mean In&Out return across asset classes was 1.72%. In this period, total market, large cap, and

mega cap ETFs underperformed the mean on average, while small cap, mid cap, and micro cap outperformed the mean on average. The worst relative performer was the total market population as it underperformed the Buy&Hold strategy by 4.45% on average. The best relative performer was the small cap population as it underperformed the Buy&Hold strategy by 1.94% on average.

During the 3-year period, the In&Out strategy displayed both outperformance and underperformance across the different categories of market capitalization. The mean describes that the average relative performance between the In&Out strategy and the Buy&Hold strategy was an underperformance of 0.18%. While the mean Buy&Hold return across asset classes was 5.82%, the mean In&Out return across asset classes was 5.63%. The mid cap and small cap ETFs outperformed the mean by a substantial margin, while the rest of the categories underperformed the mean. The worst relative performer was the total market population as it underperformed the Buy&Hold strategy by 1.50% on average. The best relative performer was the mid cap population as it outperformed the Buy&Hold strategy by 1.35% on average.

During the 1-year period, the In&Out strategy outperformed the Buy&Hold strategy across all categories of market capitalization, on average. The mean describes that the average relative performance between the In&Out strategy and the Buy&Hold strategy was an outperformance of 6.74%. While the mean Buy&Hold return across asset classes was -10.14%, the mean In&Out return across asset classes was 3.40%. The mid cap, small cap, and micro cap ETFs significantly outperformed the mean on average, while the total market, large cap, and mega cap ETFs significantly underperformed the mean on average. The worst relative performer was the total market population as it outperformed the

Buy&Hold strategy by 0.94% on average. The best relative performer was the small cap population as it out performed the Buy&Hold strategy by 14.41% on average.

## Hypothesis Testing

This study has two levels of hypotheses, with three hypotheses in each level. In the first level, one hypothesis ($H_1$) supposes that the mean return of the In&Out strategy will be less than the mean return of the Buy&Hold strategy. In this case, the null hypothesis ($H_{01}$) supposes that the mean returns of the two strategies will be equal, meaning that the trading algorithm neither outperforms nor underperforms the Buy&Hold strategy with statistical significance. In order to test this hypothesis, we use SPSS Statistics to run four difference in mean tests (t-tests).

### Difference in Means Tests

**Table 6** illustrates the results of the difference tests between the In&Out and Buy&Hold strategies. The four variables displayed on the left are annual return, standard deviation, downside deviation and coefficient of variation.

**Table 6.** Independent Samples Test

| | | **In&Out** | **Buy&Hold** | | | |
|---|---|---|---|---|---|---|
| | | *Mean* | *Mean* | *Mean Difference* | *t-stat* | *p-value* |
| 1 | *Annual Return* | 7.06% | 7.94% | -0.88% | -0.525 | <0.001 |
| 2 | *Standard Deviation* | 14.43% | 18.28% | -3.84% | -5.665 | <0.001 |
| 3 | *Downside Deviation* | 13.45% | 17.71% | -4.25% | -8.755 | <0.001 |
| 4 | *Coeff. of Var. (CV)* | 3.114 | 7.244 | -4.129 | -0.89 | >0.05* |

**statistically insignificant*

In the first row, the mean annual return of the In&Out Strategy is 7.06% while the mean annual return of the Buy&Hold strategy is 7.94%. The difference is -0.88%, meaning the In&Out underperformed the Buy&Hold strategy by 0.88% on average. As illustrated by the p-value, the results of the t-test are statistically significant, so the study may reject the null hypothesis that the variance of the two populations is the same. The finding that the algorithm will underperform the Buy&Hold strategy in a 1-year period on average, is consistent with our observations throughout the study. It is presumed that the algorithm will underperform by a greater extent if examined over a longer period. Additionally, the study acknowledges the fact that the presence of the two large selloffs periods (2008 & 2018) may be inflating the mean return of the In&Out strategy. Regardless, the more the algorithm outperforms during selloffs, the greater is the value added by the strategy during such periods.

In the second row, the mean standard deviation of the In&Out strategy is 14.43% while the mean standard deviation of the Buy&Hold strategy is 18.28%. The difference is -3.844%, meaning the In&Out strategy experienced 3.844% less volatility than the Buy&Hold strategy on average. As both the p-value and t-statistic illustrate that the results of the difference test are statistically significant, the study may reject the null hypothesis that the variance of the two populations is the same. By rejecting the null hypothesis, the study concludes that the trading algorithm reduces the standard deviation of the underlying investment, compared to the Buy&Hold strategy.

In the third row, the mean downside deviation of the In&Out strategy is 13.45% while the mean downside deviation of the Buy&Hold strategy is 17.07%. The difference is -4.25%, meaning the In&Out strategy experienced 4.25% less downside deviation than

the Buy&Hold strategy on average. As both the p-value and t-statistic illustrate the results of the difference test are statistically significant, we may reject the null hypothesis that the variance of the two populations is the same. By rejecting the null hypothesis, the study concludes that the trading algorithm reduces the downside deviation of the underlying investment, compared to the Buy&Hold strategy.

The study also examines the coefficient of variation (CV) of each population, in order to compare the two strategies using a measure for risk-adjusted return. The study did not propose a hypothesis related to CV as periods of negative annual return mathematically result in negative CV values, which are often difficult to interpret. In order to create a meaningful difference test, the study eliminates all negative CV values in both samples. Thus, the difference test examines the CV of both strategies only during periods of positive annual return.

In order to structure the difference test, the study hypothesizes that the mean CV of the In&Out strategy will be lower than the mean CV of the Buy&Hold strategy.

**Table 7.** Additional Hypothesis

| **Hypothesis** | **Null Hypothesis** |
|---|---|
| $H_{CV}$: In&Out$_{CV}$ – Buy&Hold$_{CV}$ < 0 | $H_{0CV}$: In&Out$_{CV}$ – Buy&Hold$_{CV}$ = 0 |

As illustrated in the fourth row, the mean CV of the In&Out strategy is 3.114 while the mean CV of the Buy&Hold strategy is 7.244. The difference is -4.129, meaning the trading strategy reduced the CV of the Buy&Hold strategy by 4.129 on average. In other words, the algorithm experienced a lower standard deviation per unit of return achieved. For a risk averse investor who is willing to sacrifice a portion of returns to limit the

volatility of his/her investments, the moving average strategy depicted in this study is a viable trading strategy. However, as demonstrated by the p-value of this test, the study is unable to reject the null hypothesis that the CV values of the two populations are the same. The results suggest the CV values of both populations could be different, however a larger sample would be needed.

Linear Regression Analysis

In this section, the study examines factors that may be driving the out(under)performance of the algorithm relative the conventional buy and hold strategy. This study refers to this comparative performance as relative performance, which is calculated by subtracting the performance of the Buy&Hold strategy from the performance of the In&Out strategy. In doing so, the study observes the level of correlation between the relative performance of the algorithm and variables such as annual return, standard deviation, and downside deviation of the Buy&Hold strategy. In other words, the study investigates if a correlation exists between the relative performance of the In&Out strategy and the level of return achieved or risk undertaken by the Buy&Hold strategy. Our three, second-level hypotheses suggest that ($H_A$) an inverse correlation exists between relative performance and Buy&Hold strategy performance, while a positive correlation exists between relative performance and both ($H_B$) standard deviation and ($H_C$) downside deviation.

First, $H_A$ assumes that an inverse correlation exists between the relative performance of the In&Out strategy, and the annual returns of the Buy&Hold strategy. In order to test this hypothesis, the study uses SPSS Statistics software to run a linear regression using the two variables.

| Table 8. Regression Summary* | | | | | |
|---|---|---|---|---|---|
| | *Beta* | *t* | *p-value* | *r* | *r-square* |
| *(Constant)* | 3.14 | 4.809 | <0.001 | | |
| *BHreturn* | -0.507 | -17.313 | <0.001 | 0.787 | 0.619 |
| *Predictors: (Constant, BHreturn). Dependent Variable: Relative Return | | | | | |

Illustrated in blue, the results indicate a correlation coefficient (R) of .787 which indicates a strong positive correlation between the two variables. Here, the coefficient of determination ($R^2$) of .619, indicates that the regression model accounts for 61.9% of the variability of the dependent variable, and thus the model well fits the data. As the results are statistically significant, the study is able to conclude against the null hypothesis that suggests there is no correlation between these variables. However, as the correlation is positive, these results are inconsistent with our relative return hypothesis that suggests a negative correlation between these variables exists. A positive correlation between relative return and the Buy&Hold strategy return does not tell the whole story. For example, the relative performance of the In&Out strategy is higher when the Buy&Hold strategy performs worse. We will examine this relationship further in the following section.

Next, it is important to evaluate the regression beta coefficients. The beta coefficient is the degree of change in the outcome variable for every one-unit of change in the predictor variable. Because the beta coefficients of all three second-level hypotheses are statistically significant, we refer to the sign of the beta coefficient for further information. A positive beta coefficient suggests that for every one-unit increase in the predictor variable, the outcome variable will increase by the beta coefficient value. Conversely, a negative beta coefficient suggests that for every one-unit increase in the predictor variable, the outcome variable will decrease by the beta coefficient value.

Illustrated in blue is the beta coefficient of the linear regression. Here, the beta coefficient of this regression is -.507. Because the results are statistically significant, we may assume that for every one percent increase in return of the Buy&Hold strategy, the relative return decreases by 0.507%. This explains the presupposition of $H_A$ that observed a negative relationship between the relative return and the Buy&Hold return exists. This presupposition is inconsistent with the findings of the study, as the outperformance experienced by the In&Out strategy during large market selloffs is not explained by an inverse correlation between the two variables, but rather a negative beta coefficient. The following tables represent the beta coefficients of the following two regressions.

Second, $H_B$ supposes that a positive correlation exists between the relative performance of the In&Out strategy and the standard deviation of the Buy&Hold strategy. In other words, the study seeks to determine if the relative performance of the algorithm is correlated to the level of volatility experienced by the Buy&Hold strategy. In order to test this hypothesis, the study uses SPSS Statistics software to run a linear regression.

**Table 9.** Regression Summary*

| | *Beta* | *t* | *p-value* | *r* | *r-square* |
|---|---|---|---|---|---|
| *(Constant)* | -20.119 | -12.78 | <0.001 | | |
| *BHreturn* | 1.052 | 13.602 | <0.001 | 0.678 | 0.459 |

*Predictors: (Constant, BHstdev). Dependent Variable: Relative Return

Illustrated in blue, the results indicate a correlation coefficient (R) of .678 which indicates a strong positive correlation between the two variables. Here, the coefficient of determination ($R^2$) of .459, indicates that the regression model accounts for 45.9% of the variability of the dependent variable, and thus the model fits the data fairly well. As the results are statistically significant, we are able to conclude against the null hypothesis that

suggests that no correlation exists between these variables. As the correlation is positive, these results are consistent with $H_B$.

A positive correlation suggests that as the standard deviation of the Buy&Hold strategy increases, the relative performance of the algorithm increases. This is consistent with our observations of outperformance across the ETF population throughout the study. For example, the more volatile ETFs experienced a greater degree of outperformance during the selloff in the 1-year period.

Illustrated in green, the beta coefficient of this regression is 1.052. Because the results are statistically significant, the study may assume that for every one percent increase in standard deviation of the Buy&Hold strategy, the relative return increases by 1.052%. This finding is not only consistent with $H_B$ but it defines the degree to which the standard deviation affects the relative performance of the algorithm. As indicated by the study, the greater the standard deviation of the investment, the greater will be the performance of the algorithm relative to the Buy&Hold strategy.

Third, $H_C$ supposes that a positive correlation exists between the relative performance of the In&Out strategy and the downside deviation of the Buy&Hold strategy. In other words, the study attempts to determine if the relative performance of the algorithm is correlated to the level of downside volatility experienced by the Buy&Hold strategy. In order to test this hypothesis, the study uses SPSS Statistics software to run a linear regression.

**Table 10.** Regression Summary*

| | *Beta* | *t* | *p-value* | *r* | *r-square* |
|---|---|---|---|---|---|
| *(Constant)* | -20.837 | -8.684 | <0.001 | | |
| *BHreturn* | 1.127 | 8.83 | <0.001 | 0.513 | 0.263 |

*Predictors: (Constant, BHdowndev). Dependent Variable: Relative Return

The results indicate a correlation coefficient (R) of .513 which indicates a moderate positive correlation between the two variables. Here, the coefficient of determination ($R^2$) of .262 indicates that the regression model accounts for 26.3% of the variability of the dependent variable, and thus the model doesn't fit the data particularly well. However, as the results are statistically significant, the study is able to conclude against the null hypothesis that suggests there is no correlation between these variables. As the correlation is positive, these results are consistent with $H_{C.}$

A positive correlation between these two variables illustrates that as the downside deviation of the Buy&Hold strategy increases, the relative performance of the algorithm increases as well. This observation is the basis for the assertion that the algorithm observed in this study adds value to an investment strategy during periods of heightened selloffs.

Similar to the beta coefficient of the standard deviation regression, the beta coefficient of this regression is positive. In fact, it is 1.127%. Because the results are statistically significant, we may assume that for every one percent increase in the downside deviation of the Buy&Hold strategy, the relative return increases by 1.127%. This finding is not only consistent with $H_C$ but it defines the degree to which the downside deviation affects the relative performance of the algorithm. As indicated by the study, the greater the downside deviation of the investment, the greater will be the outperformance of the algorithm relative to the Buy&Hold strategy.

# CHAPTER 6

# CONCLUSION

The results of the study agree with the empirical literature that suggests markets are efficient and trend following strategies will underperform a conventional buy and hold strategy in the majority of situations (Malkiel et al., 1970; Fama et al., 1996, Hutchinson et al., 2014). In fact, the algorithm used in the study underperforms the buy and hold strategy by 0.88% during a 1-year period on average. Although it achieves less return on average, it reduces the standard deviation and downside deviation of the buy and hold strategy by 3.84% and 4.25% respectively. This means that the algorithm consistently experiences less risk and downside risk than the conventional buy and hold strategy on average.

Although the study agrees that markets are mostly efficient, the results of the study suggest that moving average strategies are capable of revealing temporary inefficiencies, especially during heightened market selloffs. For example, study illustrates that an algorithmic trading strategy based on technical indicators, when applied to exchange traded funds (ETFs), can outperform a conventional buy and hold strategy during periods of recessions and heightened market selloffs. During these periods, the level of outperformance across the testing population is correlated to the level of volatility, downside deviation, and annual return demonstrated by the buy and hold strategy across the testing population.

The study illustrates that the most volatile ETFs outperform the buy and hold strategy the most during these selloffs. For example, the 2007-2008 Financial Crisis and the fourth quarter selloff of 2018 allowed the algorithm to outperform the conventional buy and hold strategy across all ETFs during these periods. Additionally, across these periods, the algorithm outperformed the most across micro cap ETFs, while outperforming the least across total market ETFs. Excluding total market ETFs from the sample, the weighted average market capitalization of the ETFs corresponded with the outperformance of the algorithm. For example, if the ETFs are sorted by weighted average market capitalization, they are also inversely sorted by outperformance. In other words, the algorithm outperformed the buy and hold strategy more on the smaller cap ETFs than it did on the larger cap ETFs.

This is because the smaller cap ETFs experienced greater selloffs during the periods observed and were consistently the more volatile assets. While the ETFs in the population were selected based on weighted average market capitalization, the statistical models used in the study do not examine weighted average market capitalization as a variable. Instead the study employs a series of difference of mean tests to examine the hypotheses that suggest the annual returns, standard deviation, and downside deviation of the algorithm are statistically different than those of the buy and hold strategy on average. In fact, the tests illustrate that the algorithm underperforms the buy and hold strategy by 0.88% on average, while reducing the standard deviation and downside deviation of the buy and hold strategy by -3.84% and 4.25% respectively.

The study then uses a series of linear regressions to determine the level of correlation between the relative performance of the algorithm across the ETFs, with the

annual return, standard deviation, and downside deviation across the ETF population. The results of the regressions support the hypotheses that suggest that correlations exist across the three variables. In fact, this study concludes that all three variables are positively correlated to the relative performance of the algorithm.

In addition to positive correlations, standard deviation and downside deviation also exhibit positive beta coefficients during the regressions. In fact, the study illustrates that for every 1% increase in the standard deviation of the buy and hold strategy, the relative performance of the algorithm increases by 1.052% on average. Additionally, for every 1% increase in the downside deviation of the buy and hold strategy, the relative performance of the algorithm increases by 1.127% on average.

While these variables demonstrated positive regression coefficients, annual return exhibited a negative beta coefficient. In fact, the beta coefficient of the regression model is -0.507% indicating that for every 1% increase in the annual returns of the buy and hold strategy, the relative performance of the algorithm decreases by 0.507% on average. This explains the tendency for the algorithm to underperform in most situations, while also explaining the tendency for the trading algorithm to outperform the buy and hold strategy during periods of negative annual returns.

# CHAPTER 7

# DISCUSSION

The intention of this study was to examine how the performance of an algorithmic trading strategy relative to a conventional buy and hold strategy varied across portfolios of stocks. The methodology employed in this study was motivated by earlier research that examined the impact of information uncertainty on trading strategy performance, using multiple proxies such as standard deviation of returns and market capitalization among others (Han et al., 2012; Marshall et al., 2012). Both studies examined a variety of stock indices made available by the Center for Research in Security Prices (CRSP). Marshall et al. (2012) examined quintile indices organized by market capitalization and return volatility, while Han et al. (2012) examines decile indices that include other proxies for information uncertainty including analyst forecast dispersion and distant to default among others. Both studies find consistent outperformance throughout the portfolios when organizing the results by the observed proxies. For example, the trading algorithms performed the best on the portfolios with the highest level of return volatility.

The results of this study revealed no significant differences from the central findings of earlier studies. However, this study contributed to past empirical research through applying a similar methodology of Han et al. (2012) and Marshall et al. (2012) to exchange traded portfolios of stocks (ETFs), rather than stock indices. In doing so, this study illustrates that the theoretical findings of the preceding studies are consistent when examined across ETFs.

Additionally, the study hypothesized that the trading algorithm would outperform the conventional buy and hold strategy during recessionary periods and periods of heightened selloffs. In fact, the algorithm was specifically chosen based on its ability to do so. As the results of the study supported the multiple hypotheses examined, the study was able to conclude in favor of the value added to an investment strategy when one employs this trading algorithm through recessionary periods. Based on these results, the study adheres to the optimism of Jegadeesh et al. (1993) in supporting the use of trading algorithms to execute specific objective functions. In the context of this study, the specific objective function of the observed algorithm is to reduce the impact of heightened market selloffs on investment returns. This study concludes that the examined moving average crossover strategy can do so, while reducing risk and downside risk in the process.

In terms of the application of the research, the algorithm should be seriously considered by investors, today. When comparing the current bull market to its historical averages, it is defensible to suggest that the United States equity market is in its late stages of the market cycle. For example, the peak to peak market cycle averages eight years in length, while the current bull market has lasted over ten years.

Additionally, one of the most popular recessionary indicators is demonstrated by the interest rate environment in the United States, and thus the yield curve of United States Treasury securities. Specifically, when the yield curve inverts, it signals to investors that long-term debt instruments have a lower yield than short-term debt instruments of the same credit quality. There has been a historical consistency between yield curve inversions and succeeding recessionary periods. For example, excluding the most recent inversion, the United States Treasury yield curve inverted nine times since 1962. Seven of the nine

inversions were followed by a recession within 19 months. Since 1962, yield curve inversions precede recessions by 14 months on average.

In March of 2019, the yield curve inverted for the first time since 2007. Based on the historical significance of an inversion as recession indicator, it is defensible to assume that a recession will occur at some point in the near future. To a risk-averse investor interested in hedging his/her portfolio to mitigate the effect of the recession on the value of his/her investments, employing a moving average crossover strategy could be of value. Especially to the investor who is indifferent about sacrificing a portion of upside return potential in order to mitigating downside risk, a moving average crossover strategy could especially add value. A moving average crossover strategy should also be considered by the investor whose portfolio consist of particularly risky investments, as he/she will benefit the most by employing the strategy through a recession.

# CHAPTER 7

## RECOMMENDATIONS FOR FUTURE RESEARCH

In this section, the study illustrates recommendations for future iterations of the study and related works in the discipline. In doing so, it first examines the shortcomings of the study. The study acknowledges that the return numbers examined within the study may deviate from reality for a variety of reasons. To name a few, the transaction costs and tax implications of the trading strategy were not factored into returns. The consideration of these factors would negatively impact the returns of the algorithm relative to the buy and hold strategy, as the trading algorithm would result in increased transaction costs and taxation at the marginal income tax rate.

Additionally, the model examined in the study assumes that transactions were always executed at a security's open price, which might not always be true. This could have positively or negatively affected the performance of the trading algorithm relative to the buy and hold strategy. Next, the study calculates returns based on price appreciation, which may not reflect the total returns of all ETFs used in the study. Future iterations of the study should more closely examine the way the ETFs in the sample disburse dividends and capital gains to investors.

In addition to shortcomings, this study also examines areas of expansion for future research. First, future iterations of this study should incorporate the risk-free rate at multiple stages throughout the study. For example, more explanatory risk-adjusted return

calculations such as the Sharpe ratio, Treynor Ratio, and Jensen's alpha are better measures for risk-adjusted return then the coefficient of variation.

Additionally, the model used in the study is constructed in a way that allows the user to input a proxy for the risk-free rate with each back test. However, this requires the user to make an assumption of the risk-free rate, which might not be the same within each period examined. As the study examines different length periods, the model would need to be further developed to assume the correct risk-free rate based on the observed period.

In addition to the In&Out strategy, the model also examines a version of the trading algorithm that invests into a proxy for the risk-free rate while the algorithm is not in position. The model allows the user to input the risk-free rate each time the algorithm is run. Again, this presents the challenge associated with assuming the correct risk-free rate. Although the alternative version of the algorithm was not examined in this study, it is important to acknowledge that this version of the strategy increases the returns of the primary algorithm in nearly all scenarios.

While this study illustrates that a moving average crossover strategy adds value during periods of heightened selloffs, it does not examine when to begin using the strategy, and when to switch back over to a buy and hold strategy. Thus, future iterations of the study should examine the most profitable time to begin using the strategy. An interesting approach would be to employ the algorithm following different recession indicators, such as the inversion of the United States Treasury yield curve. The study might then compare the performance of the strategy across the different starting points. As illustrated in the literature review, the algorithm is likely to underperform in periods following recessions,

so it would also be important to determine when it is most profitable to return to the buy and hold strategy.

# BIBLIOGRAPHY


Barberis, Nicholas, et al. "A Model of Investor Sentiment." Jan. 1997, doi:10.3386/w5926.

Bessembinder, Hendrik, and Kalok Chan. "Market Efficiency and the Returns to Technical Analysis." *Financial Management*, vol. 27, no. 2, 1998, p. 5., doi:10.2307/3666289.

Brock, William, et al. "Simple Technical Trading Rules and the Stochastic Properties of Stock Returns." *The Journal of Finance*, vol. 47, no. 5, Dec. 1992, pp. 1731–1764., doi:10.1111/j.1540-6261.1992.tb04681.x.

Chang, Chia-Lin, et al. "Long Run Returns Predictability and Volatility with Moving Averages." *Risks*, vol. 6, no. 4, 22 Sept. 2018, p. 105., doi:10.3390/risks6040105.

Han, Yufeng, et al. "A New Anomaly: The Cross-Sectional Profitability of Technical Analysis." *SSRN Electronic Journal*, Oct. 2013, doi:10.2139/ssrn.1656460.

Hong, Harrison, et al. "Bad News Travels Slowly: Size, Analyst Coverage and the Profitability of Momentum Strategies." Feb. 1998, doi:10.3386/w6553.

Hutchinson, Mark C, and John O'Brien. "Is This Time Different? Trend-Following and Financial Crises." *The Journal of Alternative Investments*, 2014, p. 140915234745000., doi:10.3905/jai.2014.2014.1.036.

Ilomäki, Jukka, et al. "Market Timing with Moving Averages." *Sustainability*, vol. 10, no. 7, 22 June 2018, p. 2125., doi:10.3390/su10072125.

Jegadeesh, Narasimhan, and Sheridan Titman. "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations." *The Journal of Finance*, vol. 56, no. 2, Apr. 2001, pp. 699–720., doi:10.1111/0022-1082.00342.

Jegadeesh, Narasimhan, and Sheridan Titman. "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *The Journal of Finance*, vol. 48, no. 1, Mar. 1993, p. 65., doi:10.2307/2328882.

Malkiel, Burton G., and Eugene F. Fama. "Efficient Capital Markets: A Review Of Theory And Empirical Work*." The Journal of Finance, vol. 25, no. 2, 1970, pp. 383–417., doi:10.1111/j.1540-6261.1970.tb00518.x.

Marshall, Ben R., et al. "Time-Series Momentum versus Moving Average Trading Rules." *SSRN Electronic Journal*, 22 Dec. 2014, doi:10.2139/ssrn.2225551.

Merton, Robert C. “On Market Timing and Investment Performance. I. An Equilibrium Theory of Value for Market Forecasts.” *The Journal of Business*, vol. 54, no. 3, July 1981, p. 363., doi:10.1086/296137.

Olson, Dennis. “Have Trading Rule Profits in the Currency Markets Declined over Time?” *Journal of Banking & Finance*, vol. 28, no. 1, Jan. 2004, pp. 85–105., doi:10.1016/s0378-4266(02)00399-0.

Sullivan, Ryan, et al. “Data-Snooping, Technical Trading Rule Performance, and the Bootstrap.” *The Journal of Finance*, vol. 54, no. 5, Oct. 1999, pp. 1647–1691., doi:10.1111/0022-1082.00163.

Tapa, Afiruddin Tapa. “Modified Moving-Average Trading Strategy: Evidence in Malaysia Equity Market.” *International Journal of Economics and Financial Issues*, vol. 6, ser. 7, 11 Apr. 2016. *7*, doi:10.15405/epsbs.2016.08.111.

Zhu, Yingzi, and Guofu Zhou. “Technical Analysis: An Asset Allocation Perspective on the Use of Moving Averages☆.” *Journal of Financial Economics*, vol. 92, no. 3, July 2009, pp. 519–544., doi:10.1016/j.jfineco.2008.07.002.

APPENDIX A: FORMULAS

$$Smoothing\ Constant = \frac{2}{(Days+1)}$$

$$EMA_{Today} = (Price_{Today} * \left(\frac{Smoothing}{1+Days}\right) + EMA_{Yesterday} * (1 - \left(\frac{Smoothing}{1+Days}\right))$$

$$STDEV_{daily} = \sqrt{\sum \frac{\left(return_i - return_{average}\right)^2}{n-1}}$$

$$STDEV_{annual} = \sqrt{\sum \frac{\left(return_i - return_{average}\right)^2}{n-1}} * \sqrt{250}$$

$$DownDEV_{daily} = \sqrt{\sum \frac{(return_i - return_{average})^2\ where\ r_i < r_{average}}{n-1}}$$

$$DownDEV_{annual} = \sqrt{\sum \frac{(return_i - return_{average})^2 where\ r_i < r_{average}}{n-1}} * \sqrt{250}$$

$$Coefficient\ of\ Variation\ (CV) = \left(\frac{STDEV_{annual}}{Return_{annual}}\right)$$

# AUTHOR’S BIOGRAPHY

John P. Kay was born in Boston, Massachusetts on October 5, 1995. He was raised in Hingham, Massachusetts and graduated from Hingham High School in 2014, and then from the Williston Northampton School in 2015. In May of 2019, John will graduate from the University of Maine with a bachelor’s degree in Finance and a concentration in Entrepreneurship. During his time at the University of Maine, John competed on the University of Maine football team as a linebacker and long snapper, and led SPIFFY, the University of Maine student-managed investment portfolio, as the Director of Investments.