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# Examining The Predictive Power of Moving Averages in The Stock Market

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## ABSTRACT

Moving averages are common technical analysis tools which investors use to generate buy and sell calls in the stock market. The purpose of this research paper is to analyse whether common moving average techniques can reliably predict stock market behaviour. Using hypothesis testing, this paper tests whether the percentage return yielded by using moving average combinations to trade stocks in the S&P 500 index was significantly higher than a) the percentage return yielded by randomly buying and selling the stocks and b) the market percentage return. The tests were conducted for the S&P 500 stocks in four different time frames to understand the performance of moving averages during different stock market trends (uptrend, sideways trend, downtrend). Moreover, the performance of three different buying and selling techniques which use moving averages were compared. The results of the paper indicate that an investor should not use moving averages to trade stocks owing to their limited predictive power. There were only a few moving average combinations which were significantly better than randomly buying and selling. Even those few combinations could not yield higher percentage returns than the market percentage return.

## Introduction

Many investors rely on moving averages to find precise buying and selling points that result in profitable stock market investments. However, these moving average techniques must be back-tested using suitable statistical tools. This paper aims to test whether common moving average techniques can reliably predict stock market behaviour. For this, hypothesis testing will be used to test whether the percentage return yielded by using moving average techniques to buy and sell stocks is significantly higher than a) the percentage return yielded by randomly buying and selling stocks, and b) the market percentage return (the percentage return yielded if an investor buys the stock on the first day of the time frame and sells it on the last day). If the percentage return yielded by a moving average combination is significantly higher than the random percentage return as well as the market percentage return, it will be concluded that it can reliably predict stock market behaviour.

The sample of stocks chosen for the hypothesis tests will be all the stocks in the S&P 500 index. This will provide a large and varied sample on which the moving averages can be tested. The hypothesis tests will be conducted on the stocks in four different time periods. This would bring out the performance of moving average techniques during various stock market trends. The four time periods considered in this paper will be between a) 2010 and 2020 (to analyse long-term performance), b) 2019 and 2020 (to analyse performance in an uptrend), c) 2015 and 2016 (to analyse performance in a sideways trend), and d) 2008 and 2009 (to analyse performance in a downtrend).

This paper will be divided into eight sections. Section 1 will describe the three moving average techniques tested in this paper. Section 2 will provide detail on the objectives of this paper and the methodology used. Sections 3, 4, 5, and 6 will analyse the data from the hypothesis test on whether using moving averages to trade stocks yields a higher percentage return than randomly trading stocks. Section 7 will summarize the findings from sections 3, 4, 5 and 6. Section 8 will analyse the data from the hypothesis test on whether using moving averages to trade stocks yields a higher percentage return than the market return.

## Previous Works

In his book “Stocks for the Long Run”, Jeremy Seigel creates a set of trading rules using the 200-day moving average to test whether his simple moving average strategy could yield higher percentage returns than the market percentage return (Siegal, 2008, pp. 316-349). He used daily data from the Dow Jones Industrial Average (DJIA) from 1886 to 2006. He broke the large time series into multiple small fragments to test whether the moving average could beat the market return during different stock market trends. Seigel found that between 1886 to 2012, the annualized market percentage return was 9.39%, while the annualized return generated by the 200-day moving average technique was 9.73%. Moreover, he suggested that the biggest strength of the moving average was that it could avoid major market crashes, such as the October 29, 1929 (a sell call was generated 10 days before the crash), and the October 19, 1987 crash (a sell call was generated 3 days before the crash).

Like Seigel, in the 2003 book “All about market timing”, Paul Merriman tested whether a 100-day moving average could yield higher percentage returns than the market (Masonson, 2003, pp. 138-140). The data he used was from the NASDAQ index between 1972 to 2001. He concluded that the annualized market percentage return was 13.7%, while for the moving average, the annualized return was 18.9%.

In his 2013 paper, “A Quantitative Approach to Tactical Asset Allocation”, Mebane Faber compared the returns yielded by a 10-month moving average to the market percentage return in the S&P 500 index from 1901 to 2012 (Faber, 2013, p. 23). His results were similar to other studies – the moving average system yielded marginally higher returns than the market percentage returns (10.18% vs 9.32% annualized return).

However, a common criticism of the literature testing the predictive power (profitability) of trading strategies based on moving averages is the data snooping bias. Lo and MacKinlay (1990) and Vlad (2012) both stated how having access to large historical datasets can impact the results of the statistical study. For example, authors may optimize the parameters of their trading rules according to the stock and time period in which the tests are being conducted (Vlad 2012). In fact, Faber, in his 2013 paper, recognized the possibility that Seigel “already optimized the moving average by looking back over the period in which it is tested” (Faber 2013, p. 21). Thus, to avoid data snooping bias in his own work, Faber tested his trading rule not only with the 10-month moving average, but with the 3-month, 6-month, 9-month, and 12-month moving average. Faber suggested that this was a “check against optimization” – proof that he did not optimize the moving average duration based on the time period in which he was conducting the tests (Faber 2013, p. 33).

Inspired by Faber, this paper will also try to avoid data snooping bias by testing a wide range of moving average combinations. While Faber only manipulated the moving average duration within the same trading strategy, this paper will test three different trading strategies with different types of moving averages and durations (see section 1). Moreover, to avoid a bias whilst selecting the stock on which the testing will be conducted, all the stocks in the S&P 500 index will be considered. This will provide a large and varied sample for testing. Furthermore, unlike the previous works, in this paper, the percentage return yielded by the moving average techniques would not only be compared against the market percentage return but also against the percentage return yielded by randomly buying and selling the stocks.

## Section 1: Moving Average Techniques

This section shall describe the three moving average techniques which will be tested in this paper. A moving average is an average in which the body of data to be averaged moves forward with each new trading day, i.e., a 10-day moving average calculated today would consider the previous ten days, while a 10-day moving average calculated tomorrow would consider the ten days before that (Murphy, 1999, p. 195). The ***window*** of a moving average refers to the number of days to be averaged. There are three types of moving averages:

## Simple Moving Average (SMA)

A simple moving average takes the arithmetic mean of the closing prices of a stock over a specific number of days in the past (Murphy, 1999, p. 199).

$$SMA_n = \frac{\sum_{i=0}^{n-1} A_i}{n}$$

where: $A_i$ is the closing price $i$ days before today, and $n$ is the number of days to be averaged (the window).

## Linearly weighted Moving Average (WMA)

A linearly weighted moving average assigns a heavier weighting to current data points (Murphy, 1999, p. 199).

$$WMA = \frac{\sum_{i=0}^{n-1} A_i \times (n-i)}{\frac{n(n+1)}{2}}$$

where: $A_i$ is the closing price $i$ days before today, and $n$ is the number of days to be averaged (the window).

## Exponentially Smoothed Moving Average (EMA)

An exponential moving average also assigns a heavier weighting to more current data points (similar to WMA). However, unlike the WMA (where only the previous $n$ days' prices are considered), the EMA considers all of the closing price data in the life of the stock (Murphy, 1999, pp. 199-200).

$$EMA_t = \left[A_0 \times \left(\frac{s}{1+n}\right)\right] + EMA_y \times \left[1 - \left(\frac{s}{1+n}\right)\right]$$

where:
$EMA_t$ = EMA today, $A_0$ = Today's closing price, $EMA_y$ = EMA yesterday, $s$ = Smoothing factor $\left(\frac{2}{n+1}\right)$, and $n$ = number of days to be averaged (the window)

Using these three types of moving averages, there can be many different buying/selling techniques formulated. The three considered in this paper are given below:

## Technique #1 – Closing Price Crossover

Using technique #1, one buys the stock when the daily closing price moves higher than the moving average line, and one sells the stock when the daily closing price moves below the moving average line (Murphy, 1999, pp. 238-240). This can be seen diagrammatically in figure 1.

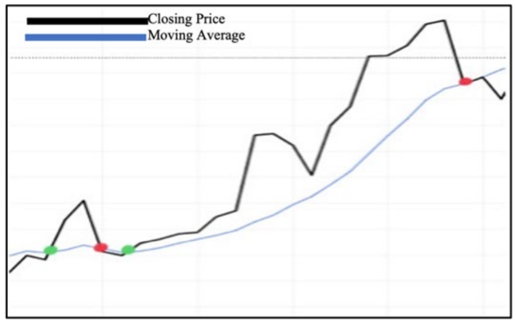


**Figure 1.** Buy signals are indicated in green, while sell signals are indicated in red. The shown stock is a daily chart of the company 'Tesla' (ticker: TSLA) from 01/07/22 to 19/08/22

For technique #1, one could either use SMA, EMA, or WMA. Even the window of the moving average could vary. The set of windows tested in this paper will be $W_1 = \{5,10,20,40,100\}$. Thus, the total number of moving average combinations which will be tested for technique #1 would be 15 (5 windows for SMA, 5 windows for WMA, and 5 windows for EMA)

## Technique #2 – Double crossover method

In technique #2, there are two moving averages involved – one with a shorter window and one with a longer window. One buys the stock when the shorter moving average crosses above the longer moving average, and one sells the stock when the shorter moving average crosses below the longer moving average (Murphy, 1999, pp. 240-241). This is demonstrated diagrammatically in figure 2.

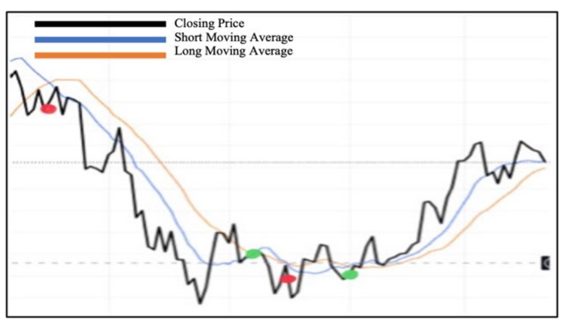


**Figure 2.** Buy signals are indicated in green, while sell signals are indicated in red. The shown stock is a daily chart of the company 'Tesla' (ticker: TSLA) from 05/04/22 to 19/08/22

Again, one can use either SMA, EMA, or WMA for both the moving averages. However, this paper will stick to the case where both, the short and long moving average belongs to the same type of moving average. The set of windows for the short moving average tested will be $S_2 = \{5,10,13,20,50\}$, while the set of windows for the long moving average tested will be $L_2 = \{20,40,49,100,200\}$. The combinations of windows for the short and long moving averages considered in this paper will be from the set $C_2 = \{(s_2, l_2) \mid s_2 \in S_2, l_2 \in L_2, l_2 > s_2\}$. Thus, the total number of moving average combinations belonging to technique #2 tested will be 63 (21 with SMA, 21 with WMA, and 21 with EMA)

## Technique #3 – Triple crossover method

In technique #3, there are three moving averages involved – one with a shorter window, one with a medium window, and one with a longer window. One buys the stock if the short moving average is less than both, the medium and long moving average, and then in the next 5 days, if it becomes greater than both the medium and long moving averages. One sells the stock if the short moving average is greater than both, the medium and long moving averages, and within the next 5 days, if the short moving average becomes less than both, the medium and long moving average (Murphy, 1999, pp. 242-244). This is shown diagrammatically in figure 3.

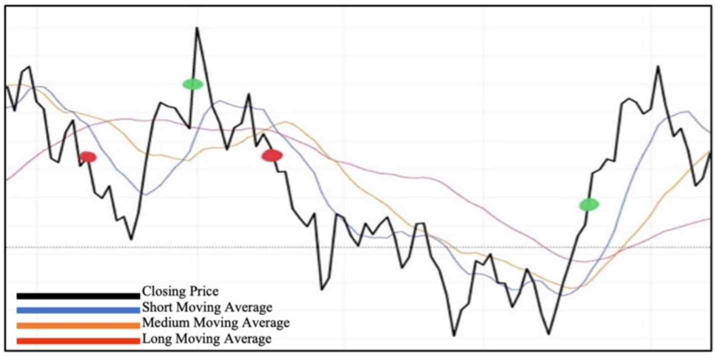


**Figure 3.** Buy signals are indicated in green, while sell signals are indicated in red. The shown stock is a daily chart of the company 'Tesla' (ticker: TSLA) from 24/11/21 to 13/04/22

Again, one could use either SMA, EMA, or WMA for all three moving averages. However, this paper will stick to the case where all three moving averages belong to the same type of moving average. The set of windows for the short moving average tested will be $S_3 = \{4,5,10,13,20,50\}$, the set of windows for the medium moving average tested will be $M_3 = \{9, 10, 20,40,49,100\}$, while the set of windows for the long moving average tested will be $L_3 = \{18, 20, 40,80,100,200\}$. The combinations of windows for the short, medium, and long moving averages considered will be from the set $C_3 = \{(s_3, m_3, l_3) \mid s_3 \epsilon S_3, m_3 \epsilon M_3, l_3 \epsilon L_3, l_3 > m_3 > s_3\}$. Thus, the total number of moving average combinations belonging to technique #3 tested will be 228 (76 with SMA, 76 with WMA, and 76 with EMA)

In total, 306 different moving average combinations $(15 + 63 + 228)$ will be tested in this paper. This paper will test whether an investor should use any of these moving average combinations to buy and sell stocks. Section 3 describes the methodology through which the combinations will be tested.

## Notation used

The notation used to denote the above techniques will be as follows:

- The first letter denotes the type of moving average used (S denotes a simple moving average, W denotes a weighted moving average, while E denotes an exponential moving average)
- The number after the first letter denotes which buying and selling technique is used (out of the three above)
- The list in the subscript denotes the windows of the moving averages in ascending order
  *For example,*
- $S3_{10,20,40}$ refers to technique #3 with simple moving averages wherein the short, medium, and long moving averages have windows of 10, 20, and 40 respectively
- $W1_{100}$ refers to technique #1 with a weighted moving average where the window is 100

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- $E2_{50,100}$ refers to technique #2 with exponential moving averages wherein the short and long moving averages have windows of 50 and 100 respectively.

If the windows are not specified in the subscript, the notation refers to all the moving average combinations which belong to the technique and type of moving average specified.

*For example,*

- S1 collectively refers to all the 5 moving average combinations which use technique #1 with a simple moving average.
- E3 collectively refers to all the 76 moving average combinations which use technique #3 with an exponential moving average.

## Section 2: Research Objectives and Methodology

The first objective of this paper is to test whether the 306 moving average combinations described in section 1 have any predictive power during different stock market trends (uptrend, sideways trend, downtrend). To achieve this, each moving average combination will be considered individually, and the percentage return it generates with each stock in the S&P 500 index will computed as a list (See appendix A for how the percentage return was calculated). Similarly, random buy and sell calls will be generated for each stock, and the percentage return yielded by random buying and selling will be computed as a list. (Note: the number of random buy and sell calls will equal the number of buy and sell calls generated by the moving average combination. This is necessary to accurately compare the percentage return yielded by the moving average combination and the random percentage return).

Next, a two-sample t-test will be conducted to test if overall (for all stocks in the S&P 500 index), the mean percentage return generated by the moving average combination is significantly higher than the mean percentage return generated by randomly buying. The two-sample t-test will be conducted for each moving average combination in four different time periods. This will help evaluate the performance of the moving average combinations during different stock market trends. The time periods considered will be:

1. Long-term (2010 – 2020) – Growth of the S&P 500 index in this period was $189.351\%$
2. Uptrend (2019-2020) - Growth of the S&P 500 index in this period was $30.433\%$
3. Sideways trend (2015-2016) - Growth of the S&P 500 index in this period was $-0.727\%$
4. Downtrend (2008-2009) - Growth of the S&P 500 index in this period was $-38.469\%$

For example, suppose the two-sample t-test is being conducted for $S1_5$ in the 10-year time period. In that case, we will first generate a list of the percentage returns $S1_5$ yields for each stock in the S&P 500 index (from 2010-2020), and another list of the percentage returns yielded by random buying and selling each stock in the S&P 500 index (again, from 2010-2020). Then, we will compare the means of both lists using a two-sample t-test to test whether the mean percentage return yielded by using $S1_5$ to buy and sell stocks between 2010 and 2020 was higher than the percentage return yielded by randomly buying and selling the stocks. The same process will be repeated for all moving average combinations in all the four time periods.

However, a two-sample t-test assumes that the data is normally distributed, while the percentage return and random percentage return data for all moving average combinations in all time periods were approximately lognormally distributed (Figure 4).

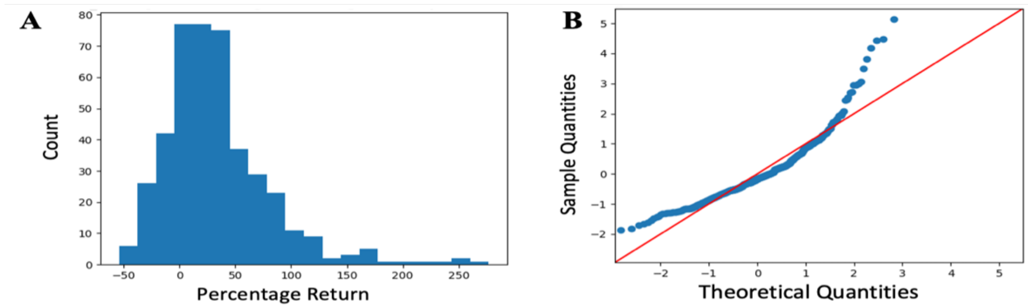


**Figure 4.** Plot A and B show the histogram and quantile-quantile (QQ) plot for the percentage return data for $S1_5$ in the 10-year time. It is clear that the shape of the data resembles a lognormal distribution. (Refer to Appendix B for Histograms and QQ plots of the percentage returns and random percentage returns for all the moving average combinations in all four time periods.)

Let $P_i$ denote the percentage return for the $i^{th}$ stock in the set of percentage returns for a given moving average combination in a given time period.

$$P_i = lognormal(\bar{p}, s_1^2)$$

Let $R_i$ denote the percentage return for the $i^{th}$ stock in the set of random percentage returns for the same moving average combination in the same time period.

$$R_i = lognormal(\bar{r}, s_2^2)$$

Thus, as per the rules of lognormal distribution (Zhou et al., 1997, p. 2):

$$\ln P_i = N\left(\bar{p}^*, {s_1^*}^2\right)$$
$$\ln R_i = N\left(\bar{r}^*, {s_2^*}^2\right)$$

However, since some of the percentage returns and random percentage returns were negative numbers, the natural logarithm of the data could not be taken directly. As a workaround, a hundred was added to each element in both the datasets and then the natural logarithm of each element in the new dataset was taken. Now:

$$P_i + 100 = lognormal(\bar{p} + 100, s_1^2)$$
$$R_i + 100 = lognormal(\bar{r} + 100, s_2^2)$$

Hence:

$$\ln(P_i + 100) = N(\mu_1, \sigma_1^2)$$
$$\ln(R_i + 100) = N(\mu_2, \sigma_2^2)$$

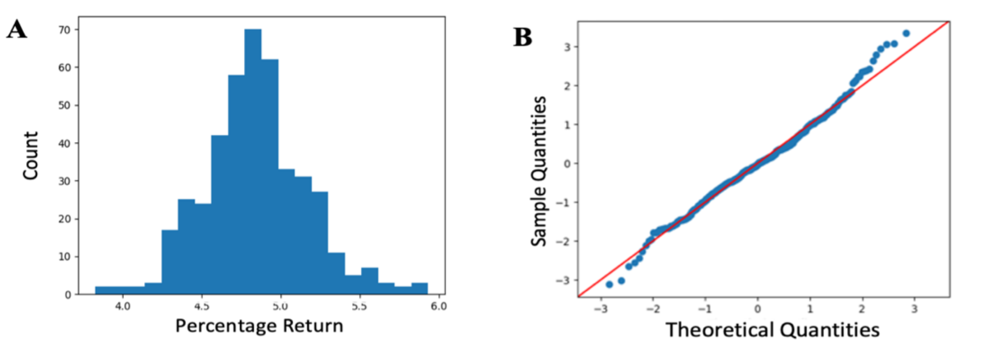

**Figure 5.** Plot A and B respectively show the histogram and quantile-quantile (QQ) plot for the percentage return data for $S1_5$ in the 10-year time after adding 100 to both datasets and taking the natural logarithm of each element. It shows how the originally lognormally distributed datasets (refer to figure 4) now became roughly normally distributed. Histograms and QQ Plots for the percentage returns and random percentage returns after this log-transformation for all the moving average combinations in all four time periods are given in Appendix B.

The ideal null and alternative hypotheses to be investigated through the two sample t-test are:

$$H_0: \bar{p} = \bar{r}$$
$$H_A: \bar{p} > \bar{r}$$

However, since the t-test cannot be performed on a lognormally distributed dataset, it shall be performed on $\ln(P_i + 100)$ and $\ln(R_i + 100)$ (since those datasets are normally distributed). Then, the same $p$ value shall be used to either reject or not reject the null hypothesis $H_0$.

However, when performing the test on $\ln(P_i + 100)$ and $\ln(R_i + 100)$, the actual null and alternate hypotheses being tested will be (Zhou et al., 1997, p. 2):

$$H_0^*: \mu_1 = \mu_2$$
$$H_A^*: \mu_1 > \mu_2$$

Note that $\bar{p}$ is a function of $\mu_1$ and $\sigma_1^2$, while $\bar{r}$ is a function of $\mu_2$ and $\sigma_2^2$ (Zhou et al., 1997, p. 2).

$$\ln(\bar{p} + 100) = \mu_1 + \frac{\sigma_1^2}{2}$$
$$\ln(\bar{r} + 100) = \mu_2 + \frac{\sigma_2^2}{2}$$

Thus, $H_0^*$ and $H_A^*$ can be written as:

$$H_0^*: \ln(\bar{p} + 100) - \frac{\sigma_1^2}{2} = \ln(\bar{r} + 100) - \frac{\sigma_2^2}{2}$$
$$H_A^*: \ln(\bar{p} + 100) - \frac{\sigma_1^2}{2} > \ln(\bar{r} + 100) - \frac{\sigma_2^2}{2}$$

These are the actual hypotheses we will be testing if conducting the t-test on $\ln(P_i + 100)$ and $\ln(R_i + 100)$. However, in the case of this test, since $\frac{\sigma_1^2}{2} \ll \ln(\bar{p} + 100)$, and $\frac{\sigma_2^2}{2} \ll \ln(\bar{r} + 100)$ (refer to appendix C for proof), $H_0^*$ and $H_A^*$ can be *approximated* as:

$$H_0^*: \ln(\bar{p} + 100) = \ln(\bar{r} + 100)$$
$$H_A^*: \ln(\bar{p} + 100) > \ln(\bar{r} + 100)$$

Thus, if null hypothesis $H_0^*$ is rejected, $H_A^*$ is accepted. $H_A^*$ states that $\ln(\bar{p} + 100) > \ln(\bar{r} + 100)$, which implies that $(\bar{p} + 100) > (\bar{r} + 100)$, which further implies that $\bar{p} > \bar{r}$. This was the original null hypothesis $H_0$ which was to be tested in the first place.

In summary, in this paper, each of the four time periods will be considered individually. For each moving average combination within that time frame, a hundred will be added to the list of percentage returns and random percentage returns. Then, a two-sample t-test will be performed on the natural logarithm of those lists to test whether the percentage return yielded by the moving average combination is significantly higher than the percentage return yielded by randomly buying. Although the p-value generated through this approach is not exact, it is an extremely good approximate, as described earlier.

The significance (alpha) level used for the test will be 0.05, and it will be a right-tailed test. Thus, if the p-value resulting from the two sample t-test is less than 0.05, null hypothesis $H_0$ will be rejected and alternative hypothesis $H_A$ will be accepted. Thus, it will be concluded that using the moving average combination to buy and sell stocks is better than randomly buying, and that the combination holds predictive power.

Sections 3, 4, 5 and 6 will analyse the data resulting from the two-sample t-test between the periods 2010 and 2020, 2019 and 2020, 2015 and 2016, and 2008 and 2009 respectively. This will draw conclusions about the predictive power of all the moving average combinations during different market trends.

The second test which will be conducted in this paper will test if the percentage return yielded by the moving average combinations is higher than the market return (the percentage return generated if an investor buys a stock at the beginning of the time frame and sells it on the last day). To achieve this, for all four time periods, a list of market percentage returns will be generated for each stock in the S&P 500 index. The format of the resulting raw data table is shown in table 1.

**Table 1.** Raw data table for the second test

| | Market Percentage Return | | | |
|---|---|---|---|---|
| Stock | Long term (2010-2020) | Uptrend (2019-2020) | Sideways trend (2015-2016) | Downtrend (2008-2009) |
| 3M | | | | |
| A.O. Smith | | | | |
| Abbott Laboratories | | | | |
| … | | | | |

Then, for each time period, each moving average combination will be considered individually, and a two sample t-test will be conducted to test whether the percentage return returned by the moving average combination is significantly higher than the market percentage returns in that particular time period. For example, if the two sample t-test is being conducted for $S1_5$ in a 10 year time frame, the two lists being compared through the t-test would be the percentage return yielded by using $S1_5$ to trade all the stocks in the S&P 500 index, and the market percentage return for all stocks in the S&P 500 index over the 10 year time period (column 2 in table 1).

For this t-test, the null and alternative hypothesis will be as following:

$$H_0^{\#}: \mu_{MA} = \mu_{market}$$
$$H_A^{\#}: \mu_{MA} > \mu_{market}$$

Where $\mu_{MA}$ represents the mean percentage return by the moving average combination, and $\mu_{market}$ represents the mean percentage return generated by the market.

However, both, the percentage returns generated by the moving average combinations and the market percentage returns in all the time periods were approximately lognormally distributed (Appendix A). Thus, the two-sample t-test could not be conducted directly as it assumes a normally distributed dataset. To solve this problem, we will use the same logic we used for the first test. For each moving average combination, a 100 will be added to the list of percentage returns and market percentage returns, and then the two-sample t-test will be performed on the natural logarithm of those lists. The same p-value will then be used to reject or not reject the null hypothesis $H_0^{\#}$. Although the p-value generated by this approach is not exact, it is an extremely good approximate as described earlier.

The significance (alpha) level used will be 0.05, and it will be a right-tailed test. If the resulting p-value in the test is less than 0.05, it will be concluded that using the moving average combination to buy and sell stocks is better than the market percentage return. Section 8 will analyse the data for this two-sample t-test.

All the raw data tables and the python code used to generate the tables can be found in appendix D.

## Section 3

Section 3 will analyse the results of the two-sample t-test in which, for each moving average combination, it was tested whether, in a 10-year time period between 2010 and 2020, the percentage return yielded by using the moving average combination to trade stocks in the S&P 500 index was significantly higher than the percentage return yielded by randomly buying and selling the stocks. For this t-test, the null and alternate hypotheses were as follows:

$$H_0: \bar{p}_1 = \bar{r}_1 \quad (1)$$
$$H_A: \bar{p}_1 > \bar{r}_1$$

Where $\bar{p}_1$ denotes the mean percentage return generated by using the moving average combination to buy and sell stocks in the S&P 500 index between 2010-2020.
$\bar{r}_1$ denotes the mean percentage return generated by randomly buying and selling the stocks in the S&P 500 index between 2010-2020.

For example, if the two-sample t-test is being conducted for $S1_5$, we will first generate a list of the percentage returns $S1_5$ yields for each stock in the S&P 500 index (between 2010 and 2020), and another list of the percentage returns yielded by random buying and selling each stock in the S&P 500 index (again, between 2010 and 2020). Then, we will compare the means of both lists ($\bar{p}_1$ and $\bar{r}_1$ respectively) through the two-sample t-test with null and alternative hypotheses (1). The p-values referenced throughout section 3 will be for the null and alternate hypotheses (1). Table 2 shows some interesting macro data resulting from the two sample t-test.

**Table 2**. Macro data summarizing the two-sample t-test

| Metric | Value |
| --- | --- |
| Average Percentage Return for Moving Average Combinations with $p < 0.05$ | 43.235 |
| Average Percentage Return for Moving Average Combinations with $p > 0.05$ | 29.103 |
| Average Random Percentage Return for all Moving Average Combinations | 24.892 |
| Percentage of Moving Average Combinations with $p < 0.05$ | 34.31% |

Surprisingly, only 34.31% of the moving average combinations generated significantly higher percentage returns than randomly buying ($p < 0.05$). There was also a large difference between the average percentage return for moving average combinations with $p < 0.05$ and with $p > 0.05$ (a difference of 14.132%). This made it clear that some moving average combinations yielded significantly higher percentage returns than others. The reason for this discrepancy is evident in table 3.

**Table 3**. Summarizing the performance of $S1, S2, S3, W1, W2, W3, E1, E2$, and $E3$

| Moving Average Technique | Percentage of moving average combinations with $p < 0.05$ | Mean Percentage Return (%) | Mean Random percentage return (%) | Mean number of buy/sell calls | Percentage of buy calls resulting in profit (%) |
| --- | --- | --- | --- | --- | --- |
| S1 | 100.00% | 35.018 | 14.503 | 174.178 | 29.306 |
| S2 | 100.00% | 52.209 | 25.519 | 31.938 | 43.055 |
| S3 | 9.21% | 31.126 | 27.762 | 51.213 | 47.986 |
| W1 | 100.00% | 34.009 | 14.079 | 213.166 | 30.038 |
| W2 | 100.00% | 45.217 | 22.833 | 40.511 | 39.590 |
| W3 | 10.53% | 25.195 | 22.394 | 83.567 | 42.127 |
| E1 | 100.00% | 35.974 | 14.131 | 183.326 | 28.519 |
| E2 | 100.00% | 55.932 | 25.968 | 30.039 | 37.231 |
| E3 | 15.79% | 31.098 | 26.722 | 61.171 | 42.170 |

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Table 3 clearly indicates that technique #1 and #2 had more predictive power than technique #3. This is evident as the percentage of combinations with $p < 0.05$ was 100% for S1, W1, E1, S2, W2, and E2, while for S3, W3, and E3, it fluctuated between 9% and 16%. Between technique #1 and #2, technique #2 had more predictive power because S2, E2, and W2 had higher average percentage returns along with a higher percentage of buy calls giving profit when compared to S1, E1, and W1. Now, let us analyse which particular moving average combination had the highest predictive power (Table 4).

**Table 4.** Data for moving average combinations which yielded the top 5 percentage returns

| Moving Average Combination | Mean Percentage Return (%) | Percentage of buy calls giving profit (%) | Average number of buy/sell calls |
|---|---|---|---|
| $S2_{50,100}$ | 74.231 | 55.837 | 12.569 |
| $S2_{50,200}$ | 79.522 | 54.608 | 6.587 |
| $E2_{13,200}$ | 76.123 | 37.497 | 12.499 |
| $E2_{50,100}$ | 75.849 | 47.060 | 9.914 |
| $E2_{50,200}$ | 85.651 | 48.469 | 6.478 |

Unsurprisingly, the top 5 combinations belonged to technique #2. This was in line with the previous conclusion ranking it as the best technique. Surprisingly, the window of the long moving average for all the combinations was either 100 or 200 (the longest windows of the long moving average tested – refer to set $L_2$), and the window of the short moving average for 4 out of the 5 combinations was 50 (the longest window of the short moving average tested – refer to set $S_2$). Figure 6 solidifies this as an actual trend.

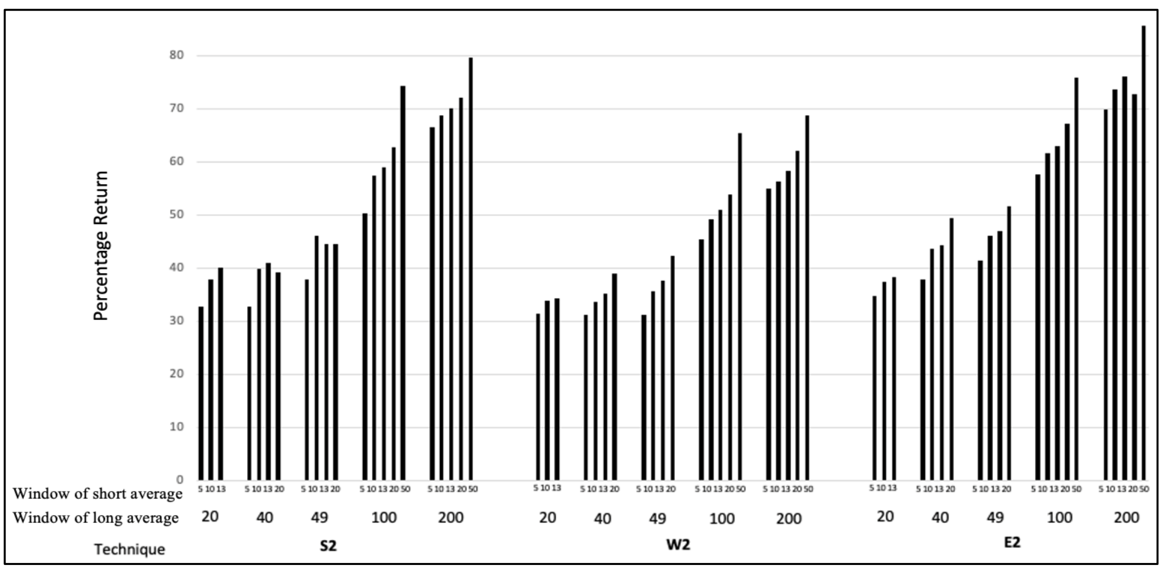


**Figure 6.** Plot showing the correlation between different combinations of windows for the short and long moving average versus the percentage return for S2, W2, and E2. Each cluster of bars belongs to a different window of the long moving average, and the individual bars within the clusters represent the windows of the short moving average plotted in ascending order. The percentage return is plotted on the y-axis.

Figure 6 clearly shows that longer windows for the long moving average results in higher percentage returns for moving average combinations belonging to S2, W2, and E2. Moreover, when the window of the long moving average is kept constant, longer windows for the short moving average result in higher percentage returns. Overall, the plot shows that within technique #2, longer windows for the short and long moving averages yield the highest returns.

Figure 7 illustrates that the percentage of buy calls resulting in profit showed no correlation with the window of the long moving average. This was counterintuitive because if longer windows for the long moving average result in higher percentage returns, one expects that the percentage of profitable buy calls will also increase with longer windows of the long moving average. However, this was not the case. Although, within the same window of the long moving average, longer windows for the short moving average resulted in a higher percentage of profitable buy calls. This was along expected lines

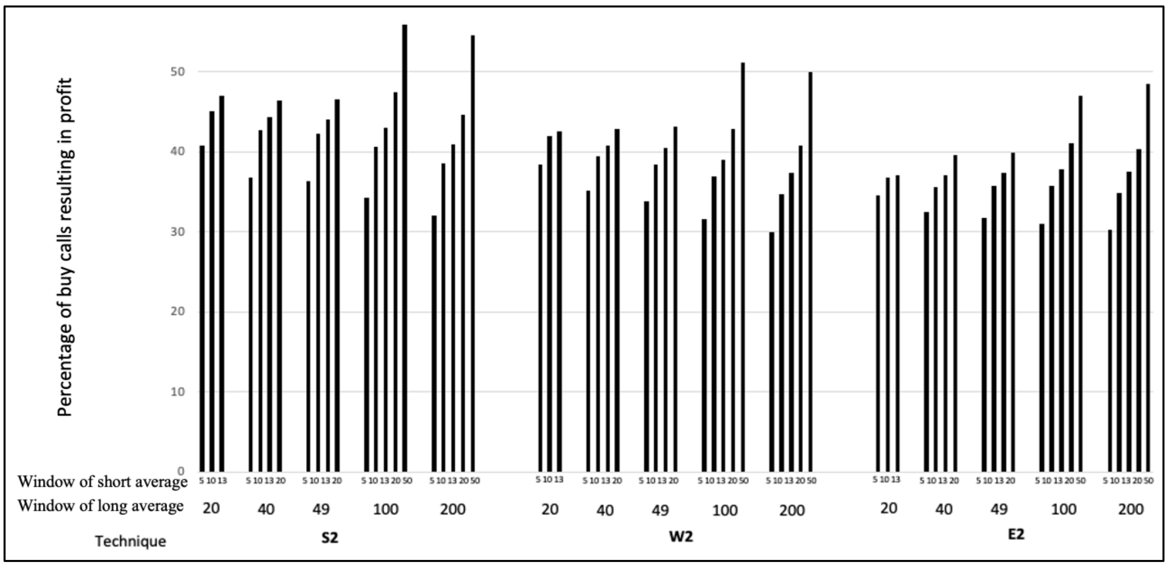


**Figure 7.** Different combinations of windows for the short and long moving averages versus percentage of buy calls resulting in profit for S2, W2, and E2

Another correlation found was the negative correlation between the window of the long moving average, and the average number of buy and sell calls. This is evident in figure 8, wherein as the windows of the long and short moving averages get longer, the average number of buy and sell calls decrease.

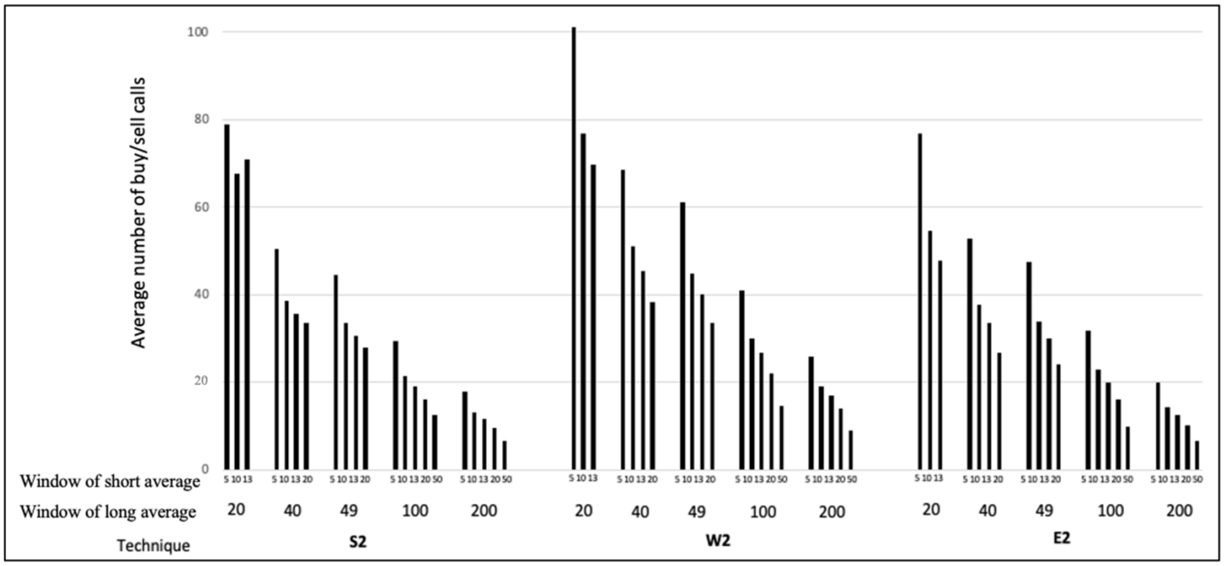


**Figure 8.** Different combinations of windows for the short and long moving averages versus average number of buy and sell calls for S2, W2, and E2

This might indicate a negative correlation between the average number of buy and sell calls, and the percentage return. Figure 9 proves that this is indeed the case.

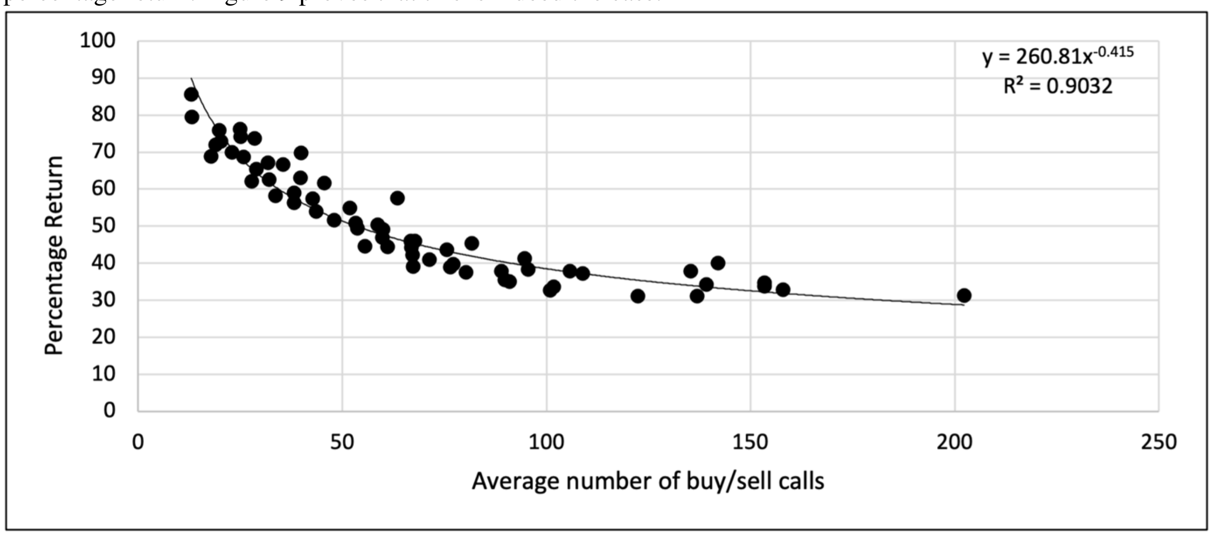


**Figure 9:** Average number of buy and sell calls versus percentage return for moving average combinations belonging to S2, E2, and W2

Figure 9 shows that as the average number of buy and sell calls decrease, the percentage return increases exponentially. This can be seen by the line of best fit $y = 260.81x^{-0.415}$. Even the $R^2$ value is 0.9032, which indicates the strength of the correlation. This result makes sense because the stocks in the S&P 500 index were mainly in an uptrend between 2010 and 2020 (as the overall growth of the S&P 500 index was 189.351%), so fewer buy and sell calls would lead to the percentage return tending towards the market return (which is high). It would be interesting to see if this correlation also exists in other market trends.

Now, let us analyse which particular moving average combination worked the best. Table 4 makes it clear that $S2_{50,200}$ and $E2_{50,200}$ are the two best combinations because they have the highest mean percentage return and the second and third highest percentage of buy calls resulting in profit respectively. In order to distinguish between $S2_{50,200}$ and $E2_{50,200}$, two 2 sample t-tests were conducted.

## Test 1

To test whether the percentage of profitable buy calls for $S2_{50,200}$ is significantly greater than the percentage of profitable buy calls for $E2_{50,200}$. For this t-test, the null and alternate hypotheses are as following:

$$H_0: PP_{S2_{50,200}} = PP_{E2_{50,200}}$$
$$H_A: PP_{S2_{50,200}} > PP_{E2_{50,200}} \quad (2)$$

Where $PP$ refers to the mean percentage of profitable buy calls.

The alpha level used was 0.05, and it was a right tailed t-test. Note: The t-test was done on the natural logarithms of $PP_{S2_{50,200}}$ and $PP_{E2_{50,200}}$ since the data was otherwise lognormally distributed. The same p-value was used to reject or not reject $H_0$. Table 5 summarizes the results of test 1.

**Table 5**. Summarizing results of test 1

| Metric | Value |
|---|---|
| T-Statistic for (2) | 4.643 |
| P-value for (2) | $1.99 \times 10^{-6}$ |
| Mean percentage of profitable calls for $E2_{50,200}$ | 48.469 |
| Mean percentage of profitable calls for $S2_{50,200}$ | 54.608 |
| Standard deviation of the percentage of profitable calls for $E2_{50,200}$ | 22.048 |
| Standard deviation of the percentage of profitable calls for $S2_{50,200}$ | 19.416 |

The p-value of $1.99 \times 10^{-6}$ for (2) was enough evidence to reject the null hypothesis $H_0$ and accept the alternate hypothesis $H_A$. Thus, $S2_{50,200}$ had a significantly higher percentage of buy calls resulting in profit than $E2_{50,200}$

## Test 2

To test whether the average percentage return for $E2_{50,200}$ was significantly greater than the average percentage return for $S2_{50,200}$. For this t-test, the null and alternative hypothesis were as following:

$$H_0: P_{E2_{50,200}} = P_{S2_{50,200}}$$
$$H_A: P_{E2_{50,200}} > P_{S2_{50,200}} \quad (3)$$

Where $P$ refers to the mean percentage return

The alpha level used was 0.05, and it was again a right tailed t-test. Note: The t-test was done on the natural logarithms of $P_{E2_{50,200}}$ and $P_{S2_{50,200}}$ since the data was otherwise lognormally distributed (refer to section 2). The same p-value was used to reject or not reject $H_0$. Table 6 summarizes the results of test 2

**Table 6**. Summarizing results of test 2

| Metric | Value |
|---|---|
| T-Statistic for (3) | 0.022 |
| P-value for (3) | 0.491 |
| Mean percentage of profitable calls for $E2_{50,200}$ | 85.651 |

| | |
|---|---|
| Mean percentage of profitable calls for $S2_{50,200}$ | 79.522 |
| Standard deviation of the percentage of profitable calls for $E2_{50,200}$ | 126.497 |
| Standard deviation of the percentage of profitable calls for $S2_{50,200}$ | 101.868 |

The p-value of 0.491 for (3) was not sufficient evidence to reject the null hypothesis $H_0$. Thus, the average return for $E2_{50,200}$ was not significantly higher than $S2_{50,200}$. Test 1 and Test 2 showed that $S2_{50,200}$ is significantly more reliable than $E2_{50,200}$ while $E2_{50,200}$ does not necessarily have a higher percentage return than $S2_{50,200}$. Thus, it can be concluded that $S2_{50,200}$ was the moving average combination with the highest predictive power in a 10-year time frame.

### Conclusions for the analysis in section 3

- Technique #2 returned higher percentage returns than technique #1, and #3 for SMA, WMA, and EMA.
- In technique #2, longer windows for the short and long moving averages yielded the highest returns.
- $S2_{50,200}$ was the moving average combination with the greatest predictive power.

## Section 4

This section will analyse the results of the two-sample t-test in which, for each moving average combination, it was tested whether, in a 1-year time period between 2019 and 2020 (where the S&P 500 index was in an uptrend), the percentage return yielded by using the moving average combination to trade stocks in the S&P 500 index was significantly higher than the percentage return yielded by randomly buying and selling the stocks. For this t-test, the null and alternate hypotheses were as follows:

$$H_0: \bar{p}_2 = \bar{r}_2 \quad (4)$$
$$H_A: \bar{p}_2 > \bar{r}_2$$

Where $\bar{p}_2$ is the mean percentage return generated by using the moving average combination to buy and sell stocks in the S&P 500 index between 2019 and 2020.
$\bar{r}_2$ is the mean percentage return generated by randomly buying and selling the stocks between 2019 and 2020.

For example, if the two-sample t-test is being conducted for $S1_5$, we will first generate a list of the percentage returns $S1_5$ yields for each stock in the S&P 500 index (between 2019 and 2020), and another list of the percentage returns yielded by random buying and selling each stock in the S&P 500 index (again, between 2019 and 2020). Then, we will compare the means of both lists ($\bar{p}_2$ and $\bar{r}_2$ respectively) through the two-sample t-test with null and alternative hypotheses (4). The p-values referenced throughout section 4 will be for the null and alternate hypotheses (4). Table 7 shows some interesting macro data resulting from the two sample t-test.

**Table 7**. Macro data resulting from the two-sample t-test

| Metric | Value |
|---|---|
| Average Percentage Return for Moving Average Combinations with $p < 0.05$ | 9.669 |
| Average Percentage Return for Moving Average Combinations with $p > 0.05$ | 7.130 |
| Average Random Percentage Return for all Moving Average Combinations | 6.515 |
| Percentage of Moving Average Combinations with $p < 0.05$ | 24.18% |

Again, only 29.27% of the moving average combinations had a mean percentage return which was significantly higher than randomly buying. Table 8 summarizes the performance of $S1, S2, S3, W1, W2, W3, E1, E2$, and $E3$

**Table 8**. Summarizing the performance of $S1, S2, S3, W1, W2, W3, E1, E2$, and $E3$

| Moving Average Technique | Percentage of moving average combinations with $p < 0.05$ | Mean Percentage Return (%) | Mean Random Percentage Return (%) | Average number of buy/sell calls | Percentage of buy calls resulting in profit (%) |
|---|---|---|---|---|---|
| S1 | 100.00% | 10.730 | 4.654 | 17.222 | 36.128 |
| S2 | 52.38% | 9.572 | 6.816 | 3.652 | 55.841 |
| S3 | 17.11% | 7.346 | 6.837 | 6.286 | 58.421 |
| W1 | 100.00% | 11.116 | 4.188 | 21.068 | 35.589 |
| W2 | 76.19% | 10.053 | 6.506 | 4.456 | 52.566 |
| W3 | 14.47% | 5.985 | 6.116 | 9.004 | 52.414 |
| E1 | 100.00% | 11.109 | 4.379 | 18.079 | 34.483 |
| E2 | 61.90% | 9.626 | 7.283 | 3.542 | 52.521 |
| E3 | 28.95% | 7.598 | 6.714 | 7.249 | 55.402 |

Table 8 suggests that techniques #1 and #2 were again better than technique #3, as the mean percentage return for S1, S2, W1, W2, E1, and E2 was significantly higher than for S3, W3, and E3. Within techniques #1 and #2, technique #1 had a consistently higher mean percentage return (although the margin is small), whereas technique #2 had a higher percentage of buy calls resulting in profit. It is now up to the investor which technique they prefer. Now, let us analyse which particular moving average combination worked the best (Table 9).

**Table 9**. Summarizing the data for combinations which yielded the top 5 percentage returns

| Moving Average Combination | Mean Percentage Return (%) | Percentage of buy calls giving profit (%) | Average number of buy/sell calls |
|---|---|---|---|
| $S1_{20}$ | 14.088 | 37.327 | 14.043 |
| $S2_{10,20}$ | 14.082 | 54.865 | 6.438 |
| $S2_{13,20}$ | 13.545 | 55.904 | 6.711 |
| $W2_{10,20}$ | 14.356 | 52.830 | 7.267 |
| $W2_{13,20}$ | 14.212 | 53.846 | 6.572 |

Unsurprisingly, the top 5 combinations belonged to either technique #1 or #2. This was in line with the previous conclusion ranking these as the best techniques. Unlike the 10 year time frame however, the long moving averages in all of the best moving average combinations belonging to S2 and W2 had windows of 20 (the lowest tested – refer to set $L_2$). Figure 10 solidifies this as a trend by showing that moving average combinations in which the long moving average has a window of 20 had a higher percentage return than other windows.

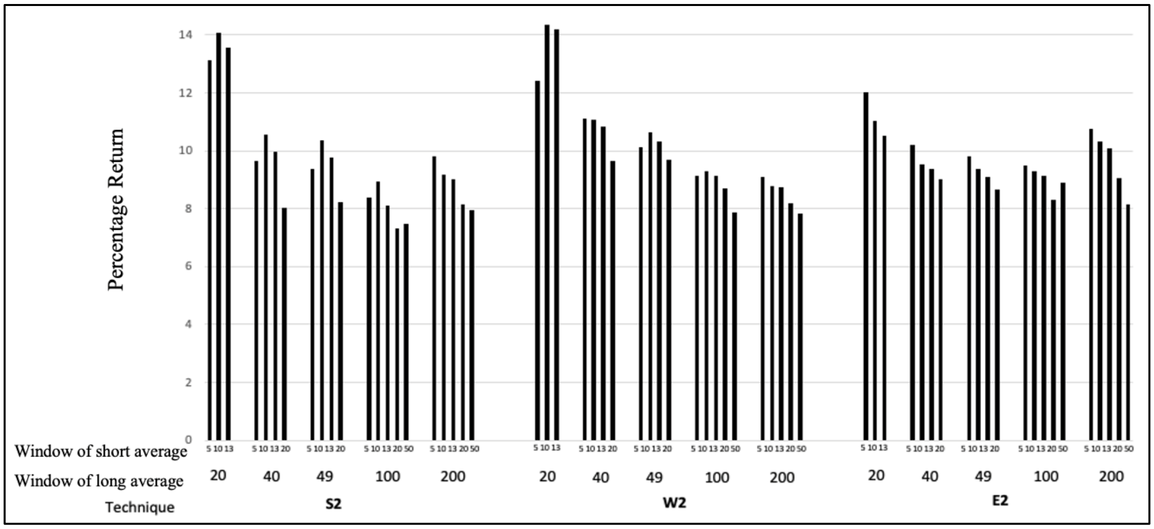


**Figure 10.** Combinations of windows for the short and long moving averages versus percentage return for all moving average combinations belonging to S2, E2, and W2

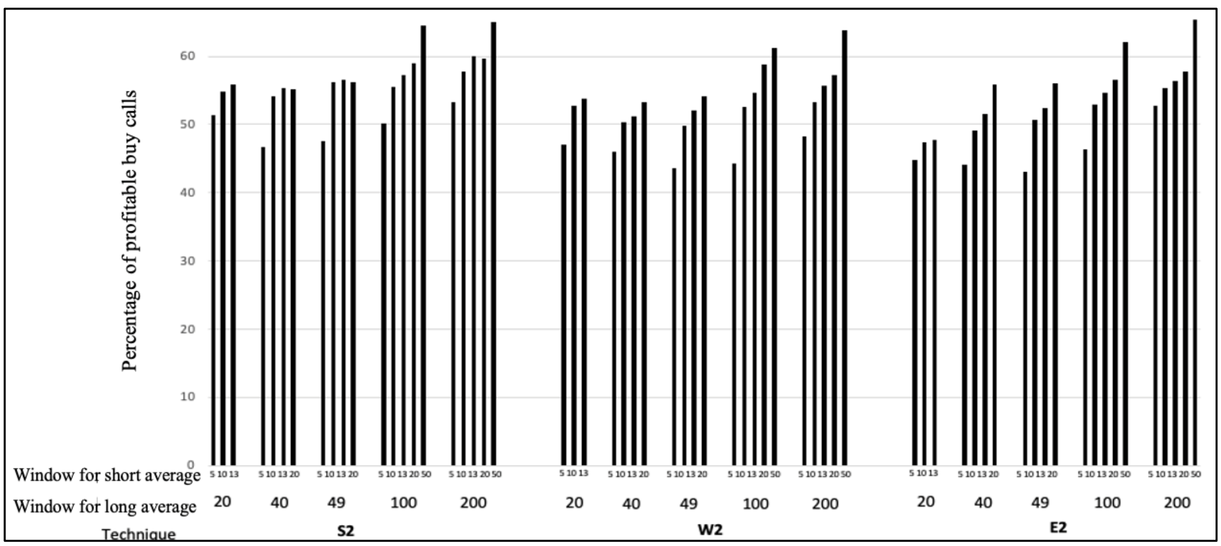


**Figure 11.** Combinations of windows for the short and long moving averages versus the percentage of profitable buy calls for all moving average combinations belonging to S2, W2, and E2

Figure 11 shows the correlation between the windows of the short and long moving averages, and the percentage of buy calls resulting in profit. It is visible that as the window of the long moving average increases, the percentage of profitable buy calls also increases (though the margin of increase is low). Moreover, when the window of the long moving average is constant, longer windows for the shorter moving average result in higher percentage of profitable buy calls. Thus, longer windows for the short and long averages result in the highest percentage of profitable calls.

Moreover, unlike the 10 year time period, the percentage return and the average number of buy and sell calls did not show a negative correlation. Instead, as the average number of buy and sell calls increased, the percentage return also tended to increase. This can be seen in figure 12.

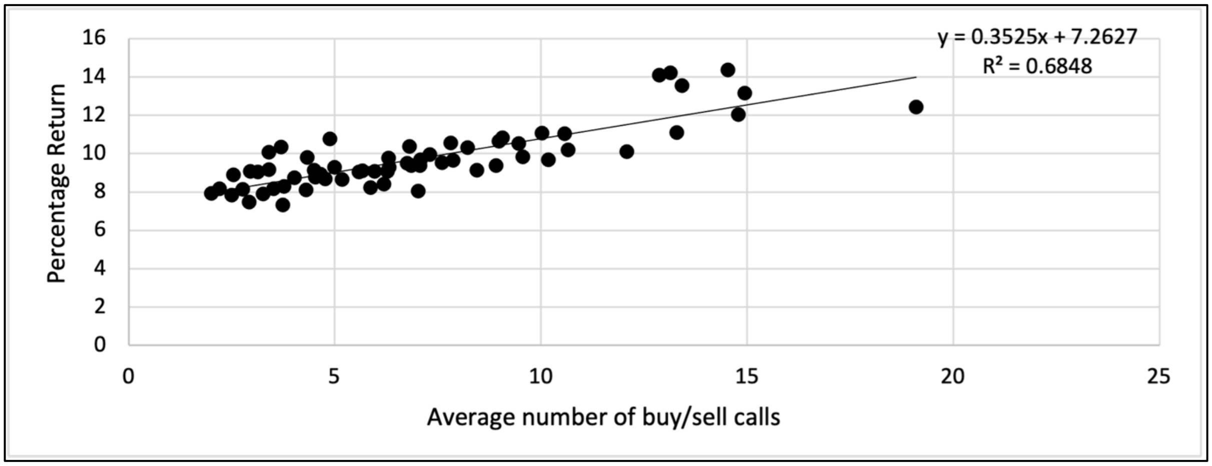


**Figure 12.** Average number of buy and sell calls versus percentage return for all moving average combinations belonging to S2, W2, or E2

This result was counterintuitive because in an uptrend, if the number of buy and sell calls are low, then the percentage return will naturally tend towards the market percentage return (which is extremely high. The S&P 500 index grew by 30.433% between 2019 and 2020).

Now, let us analyse which particular moving average combinations has the highest predictive power (Table 9). From table 9, it is easy to rule out $S1_{20}$ because compared to the other 4 combinations, it has a very low percentage of buy calls resulting in profit whilst the mean percentage return is not too different. Out of the other four combinations, it seems as if $S2_{13,20}$ can be ruled out because of the lower mean percentage return. There is nothing much to distinguish between $S2_{10,20}$, $\mathrm{W2}_{10,20}$, and $\mathrm{W2}_{13,20}$. An investor can choose any out of the three combinations.

## Conclusions for the analysis in section 4

- Technique #1 and #2 worked better than technique #3 for SMA, WMA, as well as EMA.
- Within technique #2, moving averages wherein the long moving average has a window of 20 gave the highest percentage returns.
- $S2_{10,20}$, $\mathrm{W2}_{10,20}$, and $\mathrm{W2}_{13,20}$ were moving average combinations with the highest predictive power.

# Section 5

This section will analyse the results of the two-sample t-test in which, for each moving average combination, it was tested whether, in a 1-year time period between 2015 and 2016 (where the S&P 500 index was in a sideways trend), the percentage return yielded by using the moving average combination to trade stocks in the S&P 500 index was significantly higher than the percentage return yielded by randomly buying and selling the stocks. For this t-test, the null and alternate hypotheses were as follows:

$$H_0: \bar{p}_3 = \bar{r}_3 \qquad (5)$$
$$H_A: \bar{p}_3 > \bar{r}_3$$

Where $\bar{p}_3$ is the mean percentage return generated by using the moving average combination to buy and sell stocks in the S&P 500 index between 2015 and 2016, and $\bar{r}_3$ is the mean percentage return generated by randomly buying and selling the stocks in the S&P 500 index between 2015 and 2016.

For example, if the two-sample t-test is being conducted for $S1_5$, we will first generate a list of the percentage returns $S1_5$ yields for each stock in the S&P 500 index (between 2015 and 2016), and another list of the percentage returns yielded by random buying and selling each stock in the S&P 500 index (again, between 2015 and 2016). Then, we will compare the means of both lists ($\bar{p}_3$ and $\bar{r}_3$ respectively) through the two-sample t-test with null and alternative hypotheses (5). The p-values referenced throughout section 5 will be for the null and alternate hypotheses (5). Table 10 shows some interesting macro data resulting from the two sample t-test.

**Table 10**. Macro data resulting from the two-sample t-test

| Metric | Value |
|---|---|
| Average Percentage Return for Moving Average Combinations with $p < 0.05$ | - |
| Average Percentage Return for Moving Average Combinations with $p > 0.05$ | -1.719 |
| Average Random Percentage for all Moving Average Combinations | 0.684 |
| Percentage of Moving Average Combinations with $p < 0.05$ | 0.00% |

Table 10 shows that no moving average combination yielded higher percentage returns than randomly buying in a sideways trend market. Thus, investors should never use moving averages to buy and sell stocks in a sideways trending market as even randomly buying and selling would result in higher percentage returns. A reason for this may be the ever-changing nature of a sideways market. Moving averages are a lagging indicator, so if the stock price consistently changes direction, then the signals given by the moving average are often out of date and opposite to what is required.

## Section 6

This section will analyse the results of the two-sample t-test in which, for each moving average combination, it was tested whether, in a 1-year time period between 2008 and 2009 (where the S&P 500 index was in a downtrend), the percentage return yielded by using the moving average combination to trade stocks in the S&P 500 index was significantly higher than the percentage return yielded by randomly buying and selling the stocks. For this t-test, the null and alternate hypotheses were as follows:

$$H_0: \bar{p}_4 = \bar{r}_4 \qquad (6)$$
$$H_A: \bar{p}_4 > \bar{r}_4$$

Where: $\bar{p}_4$ is the mean percentage return generated by using the moving average combination to buy and sell stocks in the S&P 500 index between 2008 and 2009.
$\bar{r}_4$ is the mean percentage return generated by randomly buying and selling the stocks in the S&P 500 index between 2008 and 2009.

For example, if the two-sample t-test is being conducted for $S1_5$, we will first generate a list of the percentage returns $S1_5$ yields for each stock in the S&P 500 index (between 2008 and 2009), and another list of the percentage returns yielded by random buying and selling each stock in the S&P 500 index (again, between 2008 and 2009). Then, we will compare the means of both lists ($\bar{p}_4$ and $\bar{r}_4$ respectively) through the two-sample t-test with null and alternative hypotheses (6). The p-values referenced throughout section 6 will be for the null and alternate hypotheses (6). Table 11 shows some interesting macro data resulting from the two sample t-test.

**Table 11.** Macro data resulting from the two-sample t-test

| Metric | Value |
|---|---|
| Average Percentage Return for Moving Average Combinations with $p < 0.05$ | -9.448 |
| Average Percentage Return for Moving Average Combinations with $p > 0.05$ | -15.016 |
| Average Random Percentage for all Moving Average Combinations | -9.500 |

| | |
|---|---|
| Percentage of Moving Average Combinations with $p < 0.05$ | 5.88% |

Only 5.88% of moving average combinations had a mean percentage return which was significantly better than randomly buying ($p < 0.05$). Table 12 summarizes the performance of $S1, S2, S3, W1, W2, W3, E1, E2$ and $E3$.

**Table 12.** Summarizing the performance of $S1, S2, S3, W1, W2, W3, E1, E2$ and $E3$.

| **Moving Average Technique** | **Percentage of moving average combinations with $p < 0.05$ (%)** | **Mean Percentage Return (%)** | **Mean Random Percentage Return (%)** | **Average number of buy/sell calls** | **Percentage of buy calls resulting in profit (%)** |
|---|---|---|---|---|---|
| S1 | 0.00% | -22.981 | -7.695 | 19.811 | 19.649 |
| S2 | 28.57% | -11.896 | -10.285 | 3.355 | 23.301 |
| S3 | 0.00% | -16.163 | -10.584 | 5.954 | 14.028 |
| W1 | 0.00% | -25.091 | -7.127 | 24.129 | 20.704 |
| W2 | 33.33% | -11.741 | -10.511 | 4.200 | 24.131 |
| W3 | 0.00% | -14.008 | -9.003 | 8.661 | 15.402 |
| E1 | 0.00% | -23.277 | -7.267 | 21.148 | 19.289 |
| E2 | 23.81% | -11.955 | -10.208 | 3.212 | 18.225 |
| E3 | 0.00% | -14.442 | -8.644 | 6.757 | 11.558 |

Again, technique #2 worked significantly better than technique #1 and #3. This is evident as the only moving average combinations with $p < 0.05$ belonged to either S2, E2, or W2. Now, let us analyse which particular moving average combination worked the best (Table13)

**Table 13.** Summarizing the data for the combinations which yield the top 5 percentage returns

| **Moving Average Combination** | **Mean Percentage Return (%)** | **Percentage of buy calls giving profit (%)** | **Average number of buy/sell calls** |
|---|---|---|---|
| $S2_{10,40}$ | -7.640 | 35.507 | 3.808 |
| $S2_{13,40}$ | -8.177 | 35.231 | 3.568 |
| $S2_{20,40}$ | -8.311 | 36.530 | 3.364 |
| $W2_{20,40}$ | -7.553 | 37.230 | 3.783 |
| $W2_{20,49}$ | -7.815 | 36.131 | 3.350 |

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Interestingly, in all the moving average combinations, the long moving average had a window of either 40 or 49. Figure 13 solidifies the fact that for S2, E2, and W2, combinations in which the long moving average had a window of 40 or 49 yielded higher percentage return than other combinations.

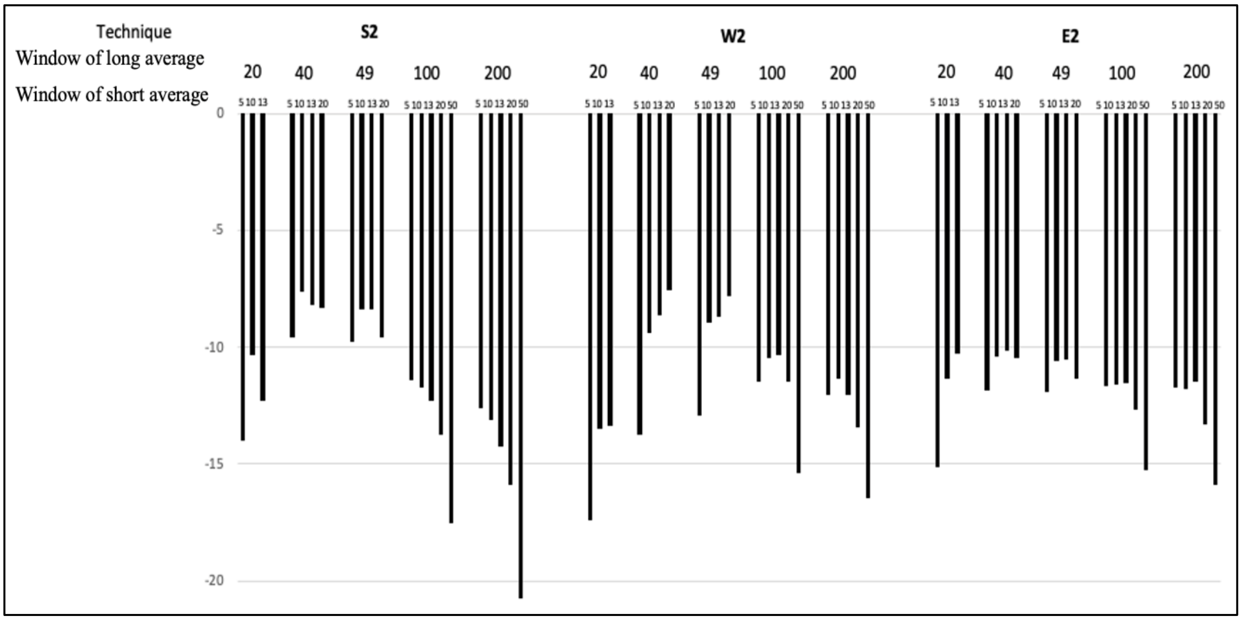


**Figure 13.** Different combinations of windows for the short and long moving average versus percentage return for all moving average combinations belonging to S2, W2, or E2

Even when it came to the percentage of profitable buy calls, moving average combinations in which the long moving average had windows of 20, 40, and 49 had the highest percentages. This can be seen in figure 14.

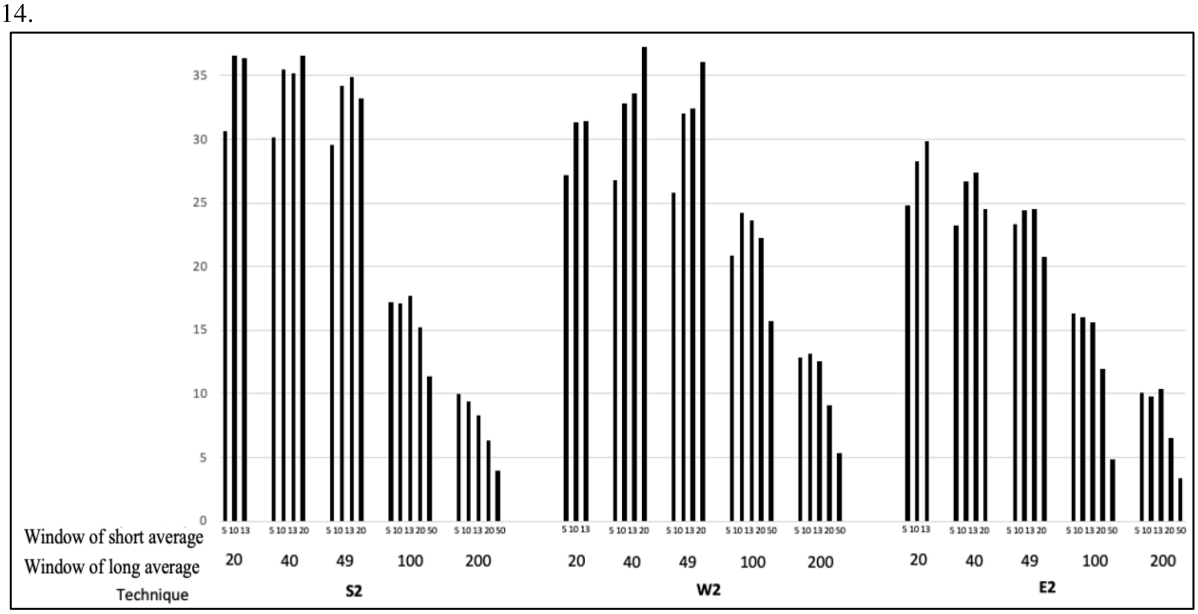


**Figure 14.** Different combinations of windows for the short and long moving averages versus percentage of buy calls resulting in profit for all moving average combinations belonging to S2, W2, or E2

When it came to the correlation between the average number of buy and sell calls and the percentage return, there was no particular correlation. This is evident in figure 15


**Figure 15.** Number of buy calls versus percentage return for all moving average combinations belonging to S2, W2, or E2

Now, let us analyse which particular moving average combination worked the best (table 13). Though there is nothing much to distinguish between the combinations, $W2_{20,40}$ was the best as it had the least negative percentage return and the highest percentage of buy calls resulting in profit.

## Conclusions for the analysis in section 7

- Technique #2 worked better than technique #1 and #3 for SMA, WMA, as well as EMA.
- Within technique #2, moving averages wherein the long moving average had windows of either 40 and 49 gave the highest percentage returns.
- $W2_{20,40}$ was the moving average combination with the highest predictive power

# Section 7: Summarizing Sections 3, 4, 5, and 6

**Table 14.** Summarizing the findings from sections 3, 4, 5, and 6

| Metric | 2010-2020 (Long-term) | 2019-2020 (Up-trend) | 2015-2016 (Sideways trend) | 2008-2009 (Downtrend) |
|---|---|---|---|---|
| Technique with most predictive power | #2 | #1 and #2 | - | #2 |
| Moving average combination with most predictive power | $S2_{50,200}$ | $S2_{10,20}$, $W2_{10,20}$, $W2_{13,20}$ | - | $W2_{20,40}$ |

The most significant finding was that technique #2 had the highest predictive power out of the three techniques.

# Section 8

This section will analyse the data from the two sample t-test which tested whether the percentage return yielded by using the moving average combinations to buy and sell stocks in the S&P 500 index is significantly higher than the market percentage return (the percentage return yielded if an investor buys the stock on the first day of the time frame and sells it on the last day) in the four different time periods. For this t-test, the null and alternate hypotheses were as follows:

$$H_0: \mu_{MA} = \mu_{market} \quad (7)$$
$$H_A: \mu_{MA} > \mu_{market}$$

Where $\mu_{MA}$ represents the mean percentage return by the moving average combination, and $\mu_{market}$ represents the mean percentage return generated by the market in the given time frame.

For example, if the two-sample t-test is being conducted for $S1_5$ for the 10-year time frame, we will first generate a list of the percentage returns $S1_5$ yields for each stock in the S&P 500 index (between 2010 and 2020), and compare its mean ($\mu_{MA}$) with the mean of the list in column 2 of table 1 ($\mu_{market}$) through the two-sample t-test with null and alternate hypotheses (7). The p-values referenced throughout section 8 will be for the null and alternate hypotheses (7). Table 15 summarizes the results of the t-test.

**Table 15.** Summarizing results of the t-test

| Time Frame | Market Percentage Returns (%) | Percentage of moving average combinations with $p < 0.05$ |
|---|---|---|
| Long term (2010-2020) | 344.038 | 0.00% |
| Short term uptrend (2019-2020) | 28.98 | 0.00% |
| Short term sideways trend (2015-2016) | 2.191 | 0.00% |
| Short term downtrend (2008-2009) | -34.994 | 100.00% |

Table 15 shows that for the long-term, short-term uptrend and short-term sideways trend, there was no moving average combination whose percentage return was significantly higher than the market returns. Thus, investors should never use moving averages in the long-term, a short-term uptrend or a short-term sideways trend. Instead, they should rely on the market to fetch high returns.

On the other hand, in a short-term downtrend market, 100% of the moving average combinations had a p-value of less than 0.05. Thus, moving average combinations could only better the market percentage return in a downtrend market. This is a major advantage of using moving average combinations, as it shows how major losses are averted. In the period between 2008 and 2009, the S&P 500 crashed due to the financial crisis in the United States. During this time, the market percentage return was -34.994%, however, the average percentage return yielded by the moving average combinations was -14.689%. Some combinations, such as $W2_{20,40}$ even yielded returns as high as -7.553%. This shows that using moving averages might help investors prevent major losses during a market crash. This was in line with Seigel's findings (refer to Previous Works section)

However, even in a short-term downtrend market, no moving average combination resulted in a positive percentage return. Moreover, 94.120% of the moving average combinations were not significantly better than randomly buying and selling stocks (refer to table 11).

## Conclusion

In conclusion, the findings in this paper suggest that an investor should not use moving average combinations to buy and sell stocks in the stock market. In a 10-year time frame (2010-2020) and an uptrend market (2019-2020), while there were some moving average combinations which were better than randomly buying, there was no moving average combination which could beat the market return. In a sideways trend market (2015-2016), there was no moving average combination which was better than randomly buying and expectedly, no moving average combination was better than the market return. In a downtrend market (2008-2009), while very few moving average combinations were better than randomly buying, all of them could beat the market return (though there were no combinations which resulted in a percentage return of greater than 0). Moreover, section

8 demonstrated that a significant advantage of using moving average combinations to trade stocks was that they help investors avert major losses during stock market crashes (such as the S&P 500 crash between 2008 and 2009)

This research can be furthered by testing a larger set of windows for all the moving averages. Moreover, within technique #2 or #3, one could take different combinations of the types of moving averages. For example, there could be a moving average combination in technique #2 where the short moving average is a simple moving average, but the long moving average is an exponential moving average. Furthermore, the performance of moving averages can be tested on different types of stocks (small-cap, mid-cap and large-cap stocks). Also, one could also use similar analytical techniques to judge the predictive power of other technical analysis tools used by investors, such as Bollinger bands, divergence, and candlestick patterns. Even algorithms which combine different technical indicators could be back-tested using the same process.

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## References

Murphy, J. J. (1999). Technical Analysis of the Financial Markets: A Comprehensive Guide to Trading Methods and Applications (SUB UPD EX ed.). New York Institute of Finance.

Zhou, X.-H., Gao, S., & Hui, S. L. (1997). Methods for Comparing the Means of Two Independent Log-Normal Samples. Biometrics, 53(3), 1129–1135. https://doi.org/10.2307/2533570

Faber, Meb (2013), A Quantitative Approach to Tactical Asset Allocation. The Journal of Wealth Management, Spring 2007, Available at SSRN: https://ssrn.com/abstract=962461

Masonson, L. (2003). All About Market Timing. McGraw Hill. ISBN: 9780071436083
(Note: Paul Merriman's research is described in this book)

Lo, A.W., MacKinlay, A.C., (1990). Data-snooping biases in tests of financial asset pricing models. Review of Financial Studies 3, 431–467.

Vlad Pavlov, Stan Hurn (2012), Testing the profitability of moving-average rules as a portfolio selection strategy,
Pacific-Basin Finance Journal, Volume 20, Issue 5, Pages 825-842, ISSN 0927-538X, https://doi.org/10.1016/j.pacfin.2012.04.003.(https://www.sciencedirect.com/science/article/pii/S0927538X12000327)

Siegel (2008), Jeremy J. Stocks for the Long Run. New York: McGraw Hill. ISBN: 978-0-07-180051-8

Trading View. https://in.tradingview.com/