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Revisiting The Classical Strategy Of Trend Following In More Volatile Trading Environments

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ABSTRACT

Trend-following strategies (TFS) have been well-established for their effectiveness in analysing stock prices for decades. However, there remains a pressing need to revisit and analyse their performance in today's increasingly volatile financial environment. First, this study investigated their profitabilities with respect to the S&P500 fund over the past 10 years. The fund's consistent and strong uptrend over the 10-year period resulted in TFS being unable to outperform the passive buy-and-hold strategy. Longer moving averages and breakout lengths were more profitable given the fund's bullish nature. Additionally, it was found that exponential moving averages were more effective than simple moving averages. The study also established that trading more frequently, such as daily, had no advantage over trading weekly or monthly. TFS incorporated with stop losses were largely ineffective and were only profitable when market prices displayed strong and consistent trends. Second, this study examined the relevance of TFS in varying economic climates by using data across various market sectors and time periods. It was found that TFS performed better when prices display both bullish and bearish trends as opposed to when prices only trend in one direction or experience frequent fluctuations. Given the steady uptrend in the S&P500 fund in recent times, the effectiveness of these strategies have deteriorated compared to the past where price patterns were less consistent. Thus, it can be said that the relevance of TFS have diminished for funds displaying consistent one-directional trends, like the S&P500 fund, or extremely volatile price patterns.

Introduction

Technical analysis is a methodology employed to identify trading or investment opportunities based on past market data, namely price and volume. Due to the immense volume of transactions and increasing volatility of market prices today, it has become more feasible to use computational approaches to do so.

TFS are widely used among trading advisors for technical analysis. Such strategies are reactive and ride on existing price patterns instead of forecasting future prices. Most prevalent approaches include calculations using prevailing price data, moving averages and breakout strategies (Fong & Tai, 2009).

It involves identifying a current market trend and trading strictly according to the pre-defined strategies, but how strategies should be formulated has become an important research problem. Rules such as when to buy and sell, as signalled from the market trend, have a direct impact on their profitabilities. TFS are guided by the current market trend (signals from the trend) and specified by the rules (reactions to the trend). A most basic TFS will be when buying and selling are cued by the conditions when the market trend, represented by its moving average, rises over an up-threshold, and falls below a down-threshold respectively. The values of the thresholds are pre-defined as a part of the trading rules (Fong et al., 2012).

Numerous studies have investigated the effectiveness of various TFS. However, prices of the S&P500 fund have become increasingly volatile as illustrated by the increased frequency and magnitude of price fluctuations, especially from 2018 onwards, in Figure 1. This could potentially have profound implications on TFS and thus underscores the necessity to revisit this issue in today's financial climate.

Figure 1. Closing Prices of S&P500 Fund from 1 January 2012 to 31 December 2022

This study primarily utilised price data for analysis, and investigated the effectiveness of various TFS on the S&P500 fund under different market conditions.

First, the study investigated the effectiveness of various strategies by analysing the profitability of:

1. Simple TFS against more sophisticated ones, including moving average (MA) and breakout strategies with modified entry or exit conditions;
2. Strategies that utilise exponential moving averages against those that utilise simple moving averages;
3. Trading using weekly or monthly moving averages against daily moving averages; and
4. Using percentage stop-losses and purchase cost stop-losses.

Next, the study examined the profitabilities of TFS in varying economic environments by applying them to:

1. Different market sectors; and
2. Consecutive 5-year periods.

Existing Literature

TFS have been widely utilised in various markets, including those of futures and commodities (Ostgaard, 2008). Some techniques have even been modified and adapted into new strategies with more innovative rules to suit the evolving financial climate (Covel, 2005). The profitability of TFS is contingent on sustained market price movements and, as such, price data is fundamental to the formulation of such strategies.

Profitability of TFS

There exists a wealth of research on the effectiveness and profitability of TFS across various markets, such as commodities (Szakmary et al., 2010 and Hurst et al., 2010), equities (Wilcox & Crittenden, 2005 and ap Gwilym et al., 2010) and currencies (James, 2003).

There are numerous reasons behind the long-standing success of TFS. These include the tendency for traders to downplay the importance of current affairs and other behavioural biases that they often succumb to, such as regret and herding (Ilmanen, 2011, Friesen et al., 2009 and Clare et al., 2016).

Studies have examined the performance of adaptive and static rules in TFS when applied to long term market movements, where they were found to return positive trading profits despite bearish price patterns (Fong & Tai, 2009). Many have concluded how TFS produce an overall better performance than the passive buy-and-hold strategy. They established that TFS were able to reduce volatility, increase Sharpe ratios, lower the maximum drawdown and provide superior risk-adjusted returns (ap Gwilym et al., 2010, Faber, 2010 and Moss et al., 2015).

Performance of TFS in Different Economic Environments

Past research has suggested that the profitability of TFS is closely related to the economic environment and price patterns. TFS tend to perform when prices trend.

TFS have been established to be more effective for market prices that demonstrate strong consistent trends with low volatility and without abrupt reversals. Further, there exists a threshold on the amount of fluctuations beyond which TFS yield losses (Hurst, 2010 and James, 2003; Fong et al., 2011).

While some research suggested that the effectiveness of these strategies vary across different market sectors and thus, a portfolio based on individual sectors instead of a market aggregate could reap more profits (Shynkevich, 2012), it has also been found that TFS were able to reap significant positive returns across all markets over subperiods of the data (Szakmary et al., 2010). Evidently, there exists much uncertainty regarding the efficacy of such strategies across various economic environments.

Summary

Given the increasing volatility and unpredictability of the financial climate and price movements today, there exists a pressing need to examine if TFS are still profitable. A recent study which delved into the effectiveness of TFS, stop losses and the frequency of trading on the S&P500 fund provided invaluable insights into the profitability of several strategies (Clare et al, 2013). Those insights have been further discussed and tested in this study.

Overall, this study aims to not only shed light on the efficacy of TFS in recent years, but also investigate whether they are still relevant today and identify the sectors in which they generate the most profits.

Methodology

Computational approaches were used to regulate automated trading where the software system decides when to buy or sell a stock from the market.

Python modules were used to perform various mathematical and data-handling functions as well as extract packages. The Yahoo finance package (yfinance) was used in this study to retrieve our stock price data. The popular Pandas package was used to convert financial time series data into suitable data structures for analysis and visualisation while Numpy was utilised to perform numerical and array calculations. Matplotlib facilitated the 2D and 3D plotting of data for further analysis. Subsequently, the effectiveness of different strategies were determined by calculating the final profits over the trading period.

Results and Discussion

Trend-Following Strategies Using Simple Moving Averages

This study first investigated the profitability of TFS which utilised simple moving averages. A simple moving average (SMA), as depicted in Figure 2 below, is calculated by adding recent price figures and dividing that sum by the number of time periods, as shown:

$$SMA = \frac{A_1 + A_2 + \cdots + A_n}{n}$$

where: A_x is the closing price at time period x and n is the total number of time periods

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Figure 2. Closing Prices of S&P500 Fund (Black Line) and its 100-day SMA (Red Line)

In this study, entry into the market referred to the beginning of investments in the S&P500 fund and earning its returns over the relevant holding period. After exiting the market, returns on cash are earned until the next entry into the market. Profits were calculated from 1 January 2012 to 31 December 2021 to provide sufficient data, both past and present, for the evaluation of the different strategies. The strategies are explained in Tables 1 and 2.

Table 1. Figures Illustrating the Entry and Exit Conditions for the Buy-and-Hold Strategy

Strategy	Figures Illustrating Entry Conditions	Figures Illustrating Exit Conditions
Buy-and-Hold		

The rationale behind these approaches stem from the fact that despite the current market price being the most relevant data point, it is unclear as to how long-ago comparisons should be drawn from (Ilmanen, 2011). Hence, MAs were used as they help to dilute the significance of any particular point but also, take into consideration all the data points in the time period.

Table 2. Figures Illustrating the Entry and Exit Conditions for Single MA Strategy, MA Crossover Strategy, MA Crossover Strategy with a Modified Exit Condition, Breakout Strategy with Entry Price Exit Condition and Breakout Strategy with MA Exit Condition

<table>
<tr><th>Strategy</th><th>Figures Illustrating Entry Conditions</th><th>Figures Illustrating Exit Conditions</th></tr>
<tr><td>Single MA</td><td>
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<tr><td>MA Crossover</td><td>
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<tr><td>MA Crossover with Modified Exit Condition</td><td>
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<tr><td>Breakout with Entry Price Exit Condition</td><td>

OR

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<tr><td>Breakout with MA Exit Condition</td><td>

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Table 3. Results for SMA Strategies

Buy-and-Hold	**Single MA**		**MA Crossover**		**MA Crossover with Modified Exit Condition**		**Breakout with MA Exit Condition**		**Breakout with Entry Price Exit Condition**	
Profits ($)	MA Length (Days)	Profits ($)	Fast/Slow MA Length (Days)	Profits ($)	Fast/Slow MA Length (Days)	Profits ($)	Breakout (Past X Days) / MA Length	Profits ($)	Breakout (Past X Days) / MA Length	Profits ($)
347.46	**10**	215.47	**25/50**	234.26	**25/50**	10.71	**10/10**	127.39	**10/10**	347.46
	25	194.38	**25/100**	184.59	**25/100**	30.91	**25 25**	104.51	**25 25**	347.46
	50	194.28	**50/100**	211.97	**50/100**	37.21	**50/50**	86.13	**50/50**	321.69
	100	181.97	**50/150**	219.74	**50/150**	145.50	**100/100**	95.53	**100/100**	324.86
	150	193.50	**50/200**	246.57	**50/200**	137.85	**150/150**	158.09	**150/150**	322.28
	200	245.58	**100/250**	249.15	**100/250**	107.13	**200/200**	170.57	**200/200**	322.28
	250	275.87	**100/300**	271.36	**100/300**	174.11	**250/250**	205.33	**250/250**	321.86
	300	263.91	**100/350**	283.50	**100/350**	176.66	**300/300**	200.13	**300/300**	321.86
	350	254.84	**100/400**	300.40	**100/400**	172.33	**350/350**	193.99	**350/350**	321.86
	400	279.07	**150/300**	305.84	**150/300**	141.12	**400/400**	213.38	**400/400**	321.86
	450	279.15	**150/350**	306.37	**150/350**	16.93	**450/450**	215.23	**450/450**	321.86

Single MA Strategy

From Table 3, it is shown that larger MA values tend to perform better, with the 450-day simple MA strategy returning the largest profits. The popular 250-day simple MA strategy, that is widely used among many traders, is also almost as profitable. These results echo those in prior studies where short-term signals gave worse returns compared to long-term signals as overtrading resulted in poorer performances (Clare et al., 2013). Another research also reported how MAs of 6 to 12 months perform significantly better than other values (Ilmanen, 2011). However, additional rules, such as a MA crossover strategy or breakout conditions may be required to improve performance.

MA Crossover Strategy

MA crossovers are able to identify price trend patterns and have the potential to signal whether price movements are likely to continue or reverse. Using a fast MA instead of the closing price also helps to smoothen out the data to avoid whipsawing and entering the market on false signals.

The results in Table 3 show that the MA crossover strategy performed better than the single MA strategy. Out of the MA values used for the crossover strategy, the 150/350- day strategy produced the best results. Similar to the single MA strategy, strategies using larger values were more profitable than those using smaller values. This is reflected in existing literature as well (Clare et al., 2013). However, the results in their study show a general trend where performances of the MA crossover strategy improves to a certain point before deteriorating slightly as the MA lengths increase. This trend is not reflected by the results of this study which shows how performance deteriorates before improving steadily as MA lengths increase.

MA Crossover Strategy with Modified Exit Condition

A modified exit condition was used for the MA crossover strategy, where the sell signal was changed to when the closing price falls below the slow MA. Given that MAs are lagging indicators as they are calculated from past data points, this modification aimed to allow earlier exits from the market before prices fell lower, thus cutting losses.

Table 3 illustrates how the modified exit condition resulted in significantly less profits than the normal MA crossover strategy. This reiterates how there is no advantage in using complicated strategies to those that are simpler as concluded in past research (Clare et al., 2013).

Breakout Strategies

Breakout strategies are able to ride on a trend's momentum and identify large price movements in advance. Once the market price breaks through a level of resistance, breakout strategies enter the trade and reap profits before the market price reaches a new high. Thus, breakout conditions were included in conjunction with the MA strategies. Two different exit conditions were studied for the breakout strategies. The first exit condition of exiting the market when closing price falls below the MA allows the trend to be followed more accurately and avoids exiting based on false signals. The other exit condition of exiting the market when the closing price falls below the entry price serves as a form of stop loss, where losses are cut to a minimum.

From Table 3, with regards to the breakout strategy with a MA exit condition, it can be seen that strategies using larger values for the breakout length and MA values return larger profits compared to those using smaller values. Exiting based on smaller MA values often resulted in whipsawing and false signals could reduce profits.

However, for the breakout strategy with an entry price exit condition, smaller values for the breakout length and MA value returned larger profits, albeit by a small amount. Due to the bullish nature and consistent trends the S&P500 fund demonstrates, smaller values allowed earlier entry into the market and there was no sell signal as the market price was constantly greater than the entry price, resulting in returns equivalent to a buy-and-hold strategy. Thus, this was more profitable than strategies that used larger values which entered the market slightly later.

The two breakout strategies returned vastly different outcomes given their exit conditions. The strategy where the sell signal was based on the entry price performed much better than that which depended on the MA value. This is due to the extremely bullish nature of the S&P500 fund in the past 10 years which cause the breakout strategy with the exit condition based on the entry price to return similar profits to a buy-and-hold strategy.

Conclusion

Despite prices being more volatile in recent years with occasional plunges, the S&P500 fund ultimately displays a strong uptrend and has rather consistent price patterns, rarely having periods of consolidation.

Therefore, out of six strategies analysed, the buy-and-hold strategy as well as the breakout strategy with the exit condition based on the entry price had the greatest returns. However, this could be limited to the S&P500 fund, which has demonstrated a bullish pattern over the past 10 years, or other stocks with similar price patterns. The MA crossover strategy also has a strong performance and has shown to be able to ride the trend of the S&P500 fund well.

In addition, larger values for MA and breakout length tend to have larger returns as they are less vulnerable to false signals caused by fluctuations in prices. This is important to note given the increased volatility of market prices in today's financial climate.

Trend-Following Strategies Using Exponential Moving Averages

The effectiveness of exponential moving averages was also studied in order to draw a comparison with strategies using SMAs. An example of this comparison is depicted in Figure 3 below. An exponential moving average (EMA) places greater weight and significance on the most recent data points based on the smoothing constant, as shown:

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

where: EMA_{Today} is the EMA value for the day, $EMA_{Yesterday}$ is the EMA value for the previous day, $Value_{Today}$ is the closing price for the day, $Smoothing$ is the value of the smoothing constant, $Days$ is the MA length in days.

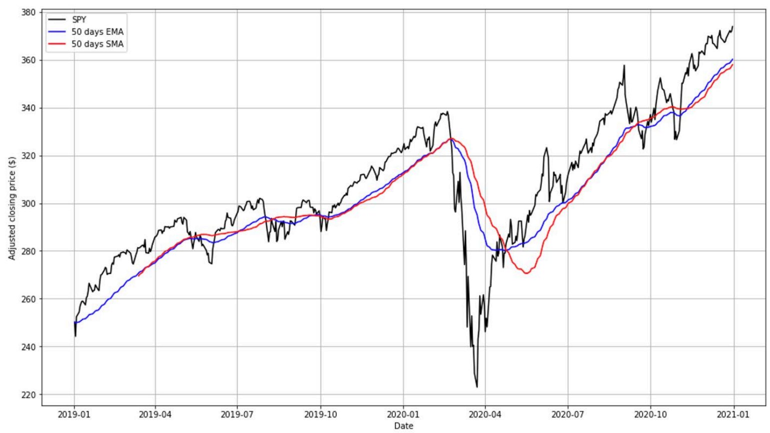


Figure 3. Closing Prices of S&P500 Fund (Black Line), its 50-day SMA (Red Line) and 50-day EMA (Blue Line)

Past Research

These rules have been investigated in academic literature where analysis of trends in stock prices used EMAs (da Costa et al., 2015, Grebenkov & Serror, 2013). Short-term investments were more profitable in the Brazilian market from 2000 to 2014 when using EMAs (da Costa et al., 2015). For the S&P500 fund from 1950 to September 2011, the 200-day and 50-day EMAs performed the best (Papailias & Thomakos, 2015).

Results and Discussion

Using the same strategies tested for SMAs earlier, profits were calculated as represented in Table 4. The results shown in Table 4 largely reflect the trends when using strategies based on SMAs. Using single MA strategy and MA crossover strategy with EMAs also showed that larger MA values returned larger profits. This is largely attributed to the recent bullish and consistent trends in the S&P500 fund as longer EMA lengths help avoid exiting the market based on false signals.

For the MA crossover strategy with a modified exit condition, slightly smaller values seemed to perform slightly better, where the 50/150-day MA returned the greatest profits compared to the 100/350-day MA for the equivalent SMA strategy.

For the breakout strategies, the results produced for EMA strategies are similar to those for SMA strategies. Larger values for both the breakout length and MA length returned larger profits for the breakout strategy with its exit condition based on the MA while the smaller values were more profitable for the breakout strategy with its exit condition based on the entry price.

Table 4. Results for EMA Strategies

Buy-and-Hold	**Single MA**		**MA Crossover**		**MA Crossover with Modified Exit Condition**		**Breakout with MA Exit Condition**		**Breakout with Entry Price Exit Condition**	
Profits ($)	MA Length (Days)	Profits ($)	Fast/Slow MA Length (Days)	Profits ($)	Fast/Slow MA Length (Days)	Profits ($)	Breakout (Past X Days) / MA Length	Profits ($)	Breakout (Past X Days) / MA Length	Profits ($)
347.46	**10**	191.91	**25/50**	278.62	**25/50**	38.98	**10/10**	145.52	**10/10**	347.46
	25	156.82	**25/100**	245.25	**25/100**	55.62	**25 25**	91.49	**25 25**	347.46
	50	156.79	**50/100**	240.88	**50/100**	2.77	**50/50**	67.65	**50/50**	321.69
	100	220.34	**50/150**	258.66	**50/150**	168.55	**100/100**	113.88	**100/100**	324.86
	150	258.69	**50/200**	235.86	**50/200**	159.35	**150/150**	176.05	**150/150**	322.28
	200	263.23	**100/250**	228.33	**100/250**	157.48	**200/200**	141.86	**200/200**	322.28
	250	265.76	**100/300**	267.13	**100/300**	142.12	**250/250**	195.77	**250/250**	321.86
	300	286.17	**100/350**	303.75	**100/350**	167.17	**300/300**	237.86	**300/300**	321.86
	350	274.36	**100/400**	327.76	**100/400**	67.37	**350/350**	236.61	**350/350**	321.86
	400	289.89	**150/300**	326.89	**150/300**	-5.74	**400/400**	227.21	**400/400**	321.86
	450	284.16	**150/350**	342.38	**150/350**	0.09	**450/450**	215.23	**450/450**	321.86

Better performances were produced when using longer MAs and breakout lengths, which is not reflective of the results shown in past studies, where their studies mentioned the greater profitability of EMA strategies when the MA lengths were shorter (da Costa et al., 2015 and Papailias & Thomakos, 2015). A possible explanation would be that EMAs of shorter lengths could react faster and more accurately to the trends. Thus, they were more profitable for the S&P500 fund in the past as well as in Brazilian markets, where prices showed frequent fluctuations and longer periods of consolidation.

Conclusion

For all 5 strategies investigated, EMA strategies performed better than SMA strategies. In placing greater emphasis on current prices, strategies using EMAs were able take advantage of the consistent and bullish nature of the S&P500 fund in entering earlier when prices rise and exiting earlier when prices fall. Despite being more vulnerable to false signals, the strong uptrend mitigated these risks when adopting strategies using EMAs. Therefore, this study concluded that EMAs can improve profitability, especially when prices are in a consistent and strong uptrend and that longer MA lengths are still more effective.

Frequency of Trading

Given the profitability of longer daily MAs in TFS, this study also investigated if there are any benefits in trading less frequently. Therefore, the single MA strategy was tested for both weekly and monthly data. This means that data was only retrieved either each week or month and MAs were calculated based on that.

Past Research

End-of-month strategies were found to produce better results in terms of higher Sharpe ratios, lower volatility as well as higher profits as compared to daily strategies (Clare et al., 2013, Annaert et al., 2009).

Results and Discussion

As can be seen from Table 5 below, the daily strategies are more profitable than weekly and monthly strategies on average. However, using the optimal MA lengths for both the weekly and monthly strategies results in better performances than the daily strategy. The 50-week strategy performed the best, followed by the 8-month strategy, and the 450-day strategy.

Table 5. Results for Daily, Weekly and Monthly Strategies

Daily Buy-and-Hold	**Daily Single MA**		**Weekly Buy-and-Hold**	**Weekly Single MA**		**Monthly Buy-and-Hold**	**Monthly Single MA**	
Profits ($)	MA Length (Days)	Profits ($)	Profits ($)	MA Length (Weeks)	Profits ($)	Profits ($)	MA Length (Months)	Profits ($)
347.46	**10**	215.47	345.45	**2**	93.90	343.64	**2**	180.16
	25	194.38		**5**	178.28		**3**	202.90
	50	194.28		**10**	198.64		**4**	173.12
	100	181.97		**15**	185.25		**5**	184.39
	150	193.50		**20**	210.01		**6**	239.25
	200	245.58		**25**	257.14		**8**	288.70
	250	275.87		**30**	244.08		**10**	272.16
	300	263.91		**40**	279.61		**12**	272.16
	350	254.84		**50**	301.58		**13**	272.16
	400	279.07		**60**	263.18		**14**	233.65
	450	279.15		**65**	257.92		**15**	256.40

Conclusion

Therefore, this study revealed that there is no advantage in trading more frequently for the S&P500 fund as weekly and monthly strategies can perform equally or even better than daily strategies, especially in recent times where prices show a consistent and strong uptrend. This conclusion resonates with past studies, where monthly strategies were found to have the best performance (Clare et al., 2013 and Annaert et al., 2009).

Stop Losses

Stop losses are orders to sell a stock when it falls to a certain price or beyond a certain threshold of loss. These rules are put in place to limit the exposure of trades to market risks and are popular strategies implemented by traders.

Past Research

There have been numerous studies on the efficacy of stop losses and in what situations they reap greater profits. However, the question still persists with divided opinions among many researchers.

In a study on several US stocks from 1970, it was found that fixed and trailing stop loss strategies can reduce the effective holding periods on losing investments. In addition, the loss reduction effect of fixed stop loss strategies was revealed to have weakened over time and that trailing stop loss strategies reduced investment risk and not investment losses (Lei & Li, 2009).

Some studies have shown how the effectiveness of stop losses can vary depending on the market and price patterns. Stop loss rules significantly reduce volatility and excessive losses, but the results vary across markets in terms of return enhancement. These rules provide higher risk-adjusted returns in bearish markets than bullish markets (Klement, 2013). For market prices that follow a random walk or are mean reverting, simple stop loss strategies always reduce expected returns. However, for market prices that demonstrate momentum in a certain direction, these strategies can be profitable (Kaminski & Lo, 2008).

There have been studies advocating the use of stop losses. It was found that losses could be reduced significantly and that average returns and Sharpe ratios were more than doubled when stop losses were incorporated with momentum strategies (Han et al., 2016). Similarly, stop-loss strategies were proven to increase the value function and that growth is larger when the asset price is close to the stop-loss level, and smaller when the price is relatively greater than that level. The study also reveals how stop-loss strategies are more effective for stocks with low growth rate and higher volatility (Yang & Zhang, 2021).

On the other hand, there has been research that proves otherwise. Both the percentage stop loss and purchase cost stop loss were found to worsen performances and that simple TFS work better when used on the S&P500 fund (Clare et al., 2013).

Results and Discussion

Given the divided opinions in the academia, this study investigates the profitability of two popular stop-loss strategies, namely the percentage stop loss and the purchase cost stop loss.

Percentage Stop Loss

Table 6. Results for 150 / 350 Day SMA Crossover Strategy (Stop Loss with Percentage Fall from Entry Price)

Percentage / %	**3**	**5**	**7**	**10**	**12**	**15**	**WITHOUT STOP LOSS**
Profits ($)	-21.84	44.58	15.76	79.52	79.52	79.52	306.37

A percentage stop loss refers to the rule where the sell signal occurs when the closing price is of a certain percentage below the entry price. In this case, several values for the percentage fall from the entry price using the 150/350-day SMA crossover strategy were tested. From Table 6, larger percentage points used for the stop loss rules were more effective than smaller values, which echoes the results from existing research (Clare et al., 2013). Values of 10 percentage points and above return the same profits as the sell signal was given by the MA crossover rule instead of the stop loss rules given that they are less strict.

It can also be concluded that the percentage stop loss is largely ineffective and erodes profits significantly as they give false signals to exit the trade despite the overall strong uptrend of the S&P500 fund. This results in the strategy losing out on profits that could have been reaped when market prices increase, only to enter the trade much later on when the fast MA crosses above the slow MA again.

Purchase Cost Stop Loss

Table 7. Results for Strategies Using Purchase Cost Stop Loss

Single MA		**MA Crossover**		**Breakout with MA Exit Condition**		**Breakout with Entry Price Exit Condition**	
MA Length (Days)	Profits ($)	Fast / Slow MA Length (Days)	Profits ($)	Breakout (Past X Days) / MA Length	Profits ($)	Breakout (Past X Days) / MA Length	Profits ($)
10	215.47	**25/50**	54.44	**10/10**	98.72	**10/10**	127.39
25	194.38	**25/100**	19.85	**25 25**	-8.92	**25 25**	104.51
50	207.86	**50/100**	23.60	**50/50**	-16.20	**50/50**	99.71
100	129.91	**50/150**	6.22	**100/100**	3.92	**100/100**	38.29
150	34.62	**50/200**	1.68	**150/150**	5.25	**150/150**	-11.59
200	34.46	**100/250**	-29.79	**200/200**	5.48	**200/200**	-31.60
250	61.82	**100/300**	-18.49	**250/250**	6.45	**250/250**	-14.70
300	34.96	**100/350**	-15.94	**300/300**	-6.03	**300/300**	-28.82
350	32.04	**100/400**	-12.44	**350/350**	-6.03	**350/350**	-28.82
400	37.89	**150/300**	-32.66	**400/400**	-4.17	**400/400**	-27.80
450	38.55	**150/350**	-8.55	**450/450**	-3.94	**450/450**	-27.73

Incorporating standard deviations into strategies has been adopted widely among traders in popular indicators such as Bollinger Bands. In this study, the profitability of purchase cost stop losses where the sell signal occurs when the closing price has fallen 2 standard deviations below the entry price was investigated. This was implemented on four strategies already examined earlier using SMAs. From Table 7, it can be seen that purchase cost stop losses are not profitable and also diminishes profits across all four strategies. It performed the best for the single MA strategy, followed by the breakout strategy using MA as its exit condition, then the breakout strategy using the entry price as its exit condition and finally the MA crossover strategy.

In addition, smaller values for the MA and breakout lengths was found to work better when the purchase cost stop loss is applied. This could be because stop loss conditions can cause trades to be vulnerable to false exit signals and strategies using shorter MA or breakout lengths can recover from these faster and re-enter the trade to earn more profits during the strong uptrend of the S&P500 fund. This is largely dissimilar to a past study which found that purchase cost stop losses still performed better when used with longer MA lengths and average breakout lengths (Clare et al., 2013).

Conclusion

The results show how stop losses are generally ineffective when incorporated into TFS as they significantly erode profits, which is corroborated by one study (Clare et al., 2013) but contrary to many other existing literature (Lei & Li, 2009, Klement, 2013, Kaminski & Lo, 2008, Han et al., 2016 and Yang & Zhang, 2021). It can also be said that stop losses perform better in strategies that use shorter MA and breakout lengths. In the case of the S&P500 fund, the purchase cost stop loss performed better than the percentage stop loss but this study draws the conclusion that a change in trend and strategies would be more profitable than stop losses.

Different Market Sectors

Given the wide array of funds available on the market for trading, it has become vital to understand which are more profitable when TFS are used.

Past Research

Technical trading rules have been found to be capable of producing superior performances for certain industry and sector portfolios in the 1990s. The proliferation of high-frequency trading and the wide acceptance of ETFs have led to a sharp and consistent increase in correlations between sectors since the early 2000s, such that actively managed trading strategies are rarely able to outperform the passive buy-and-hold approach (Shynkevich, 2012).

Results and Discussion

This study analyses the trends and effectiveness of MA strategies on nine different sectors' ETFs, namely financials (XLF), technology (XLK), industrial (XLI), materials (XLB), energy (XLE), staples (XLP), healthcare (XLV), utilities (XLU) and discretionary (XLY). This aims to understand if TFS return higher profits when used within sectors rather than on a market aggregate. The efficacy of these strategies were tested on different market sectors exhibiting varying price patterns.

Table 8. Results for MA Strategies on XLF and XLK

XLF (FINANCIALS)					**XLK (TECHNOLOGY)**				
Buy-and-Hold	**Single MA**		**MA Crossover**		**Buy-and-Hold**	**Single MA**		**MA Crossover**	
Profits ($)	MA Length (Days)	Profits ($)	Fast / Slow MA Length (Days)	Profits ($)	Profits ($)	MA Length (Days)	Profits ($)	Fast / Slow MA Length (Days)	Profits ($)
28.21	**10**	7.52	**25/50**	20.88	148.06	**10**	58.34	**25/50**	78.49
	25	12.09	**25/100**	24.41		**25**	85.50	**25/100**	106.77
	50	10.83	**50/100**	20.28		**50**	74.00	**50/100**	109.27
	100	11.41	**50/150**	17.47		**100**	85.90	**50/150**	115.14
	150	13.66	**50/200**	16.56		**150**	115.64	**50/200**	125.06
	200	20.84	**100/250**	20.20		**200**	119.99	**100/250**	132.99
	250	17.57	**100/300**	16.97		**250**	103.32	**100/300**	133.06
	300	19.51	**100/350**	14.35		**300**	107.74	**100/350**	136.27
	350	16.54	**100/400**	17.24		**350**	109.64	**100/400**	141.95
	400	12.16	**150/300**	19.06		**400**	109.31	**150/300**	134.56
	450	12.68	**150/350**	10.85		**450**	107.81	**150/350**	142.51

Table 9. Results for MA Strategies on XLI and XLB

XLI (INDUSTRIAL)					XLB (MATERIALS)				
Buy-and-Hold	**Single MA**		**MA Crossover**		**Buy-and-Hold**	**Single MA**		**MA Crossover**	
Profits ($)	MA Length (Days)	Profits ($)	Fast / Slow MA Length (Days)	Profits ($)	Profits ($)	MA Length (Days)	Profits ($)	Fast / Slow MA Length (Days)	Profits ($)
71.32	**10**	49.34	**25/50**	23.51	56.18	**10**	19.64	**25/50**	35.57
	25	30.01	**25/100**	29.74		**25**	32.64	**25/100**	15.30
	50	31.17	**50/100**	32.94		**50**	28.89	**50/100**	28.57
	100	38.87	**50/150**	33.11		**100**	27.99	**50/150**	21.83
	150	39.24	**50/200**	34.31		**150**	34.46	**50/200**	26.85
	200	49.84	**100/250**	39.45		**200**	24.82	**100/250**	36.80
	250	57.17	**100/300**	38.77		**250**	30.48	**100/300**	24.18
	300	50.27	**100/350**	36.02		**300**	33.73	**100/350**	29.44
	350	46.61	**100/400**	35.93		**350**	32.27	**100/400**	33.12
	400	40.39	**150/300**	22.39		**400**	36.17	**150/300**	30.41
	450	40.74	**150/350**	20.73		**450**	37.44	**150/350**	30.42

Table 10. Results for MA Strategies on XLE and XLP

XLE (ENERGY)					XLP (STAPLES)				
Buy-and-Hold	**Single MA**		**MA Crossover**		**Buy-and-Hold**	**Single MA**		**MA Crossover**	
Profits ($)	MA Length (Days)	Profits ($)	Fast / Slow MA Length (Days)	Profits ($)	Profits ($)	MA Length (Days)	Profits ($)	Fast / Slow MA Length (Days)	Profits ($)
-15.55	**10**	15.42	**25/50**	-1.64	44.65	**10**	22.28	**25/50**	22.41
	25	18.74	**25/100**	6.97		**25**	18.53	**25/100**	12.63
	50	24.10	**50/100**	-15.51		**50**	19.73	**50/100**	11.65
	100	-7.86	**50/150**	-7.22		**100**	22.43	**50/150**	9.04
	150	12.58	**50/200**	20.93		**150**	22.31	**50/200**	22.06
	200	14.83	**100/250**	-2.33		**200**	19.01	**100/250**	28.13
	250	10.77	**100/300**	-13.02		**250**	20.25	**100/300**	32.13
	300	15.20	**100/350**	-18.96		**300**	15.75	**100/350**	32.79
	350	5.91	**100/400**	-20.01		**350**	17.00	**100/400**	31.39
	400	-3.68	**150/300**	-2.73		**400**	24.26	**150/300**	40.99
	450	1.13	**150/350**	-5.65		**450**	21.61	**150/350**	40.44

Table 11. Results for MA Strategies on XLV and XLU

XLV (HEALTHCARE)					XLU (UTILITIES)				
Buy-and-Hold	**Single MA**		**MA Crossover**		**Buy-and-Hold**	**Single MA**		**MA Crossover**	
Profits ($)	MA Length (Days)	Profits ($)	Fast / Slow MA Length (Days)	Profits ($)	Profits ($)	MA Length (Days)	Profits ($)	Fast / Slow MA Length (Days)	Profits ($)
105.75	**10**	33.95	**25/50**	47.37	36.24	**10**	-1.82	**25/50**	-6.13
	25	48.92	**25/100**	60.18		**25**	21.54	**25/100**	-1.45
	50	37.90	**50/100**	55.42		**50**	3.49	**50/100**	10.83
	100	41.39	**50/150**	62.04		**100**	-2.14	**50/150**	5.56
	150	48.10	**50/200**	71.22		**150**	8.55	**50/200**	13.25
	200	61.43	**100/250**	94.13		**200**	3.05	**100/250**	8.83
	250	58.54	**100/300**	95.12		**250**	5.89	**100/300**	18.64
	300	58.77	**100/350**	93.64		**300**	8.38	**100/350**	22.42
	350	75.73	**100/400**	88.66		**350**	-3.63	**100/400**	18.99
	400	73.65	**150/300**	94.51		**400**	-1.06	**150/300**	17.06
	450	82.88	**150/350**	99.28		**450**	4.79	**150/350**	19.31

Table 12. Results for MA Strategies on XLY

XLY (DISCRETIONARY)				
Buy-and-Hold	**Single MA**		**MA Crossover**	
Profits ($)	MA Length (Days)	Profits ($)	Fast / Slow MA Length (Days)	Profits ($)
165.09	**10**	123.93	**25/50**	104.71
	25	102.82	**25/100**	101.86
	50	80.34	**50/100**	95.65
	100	93.24	**50/150**	96.38
	150	127.78	**50/200**	111.01
	200	134.41	**100/250**	106.87
	250	129.99	**100/300**	121.48
	300	135.61	**100/350**	136.72
	350	131.06	**100/400**	152.49
	400	147.09	**150/300**	140.06
	450	146.14	**150/350**	161.95

From Tables 8 to 12, it is found that buy-and-hold strategies are more profitable than MA strategies due to the overall uptrend in the long run for all sectors, except XLE, the energy sector, as shown in Figure 4.

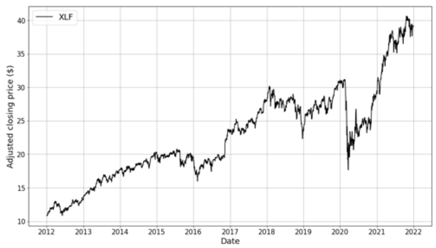
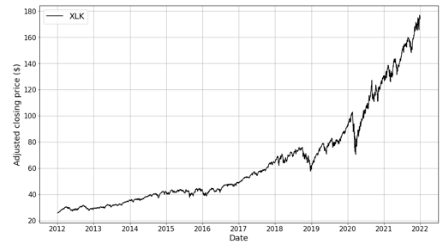
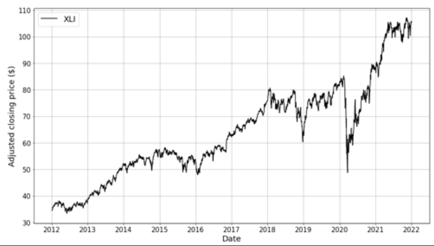
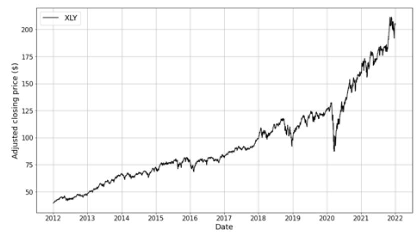
Figure 4. Closing Prices of XLE Fund

In the case of the XLE fund, the MA strategies are able to reap profits despite the overall bearish nature of market prices. The results reveal how shorter MAs are more profitable given that the market prices exhibited frequent fluctuations and periods of consolidation. Shorter MAs are able to take advantage of these patterns and make more timely decisions and changes to the trading positions.

However, with respect to the ETFs from other sectors, given the bullish nature of their market prices, the buy-and-hold strategy is the most profitable. Another discovery is how greater volatility and amounts of fluctuation in market prices leads to shorter MAs being more profitable. This is illustrated from the cases of the XLF fund (25/100-day MA crossover strategy) and the XLI fund (250-day single MA strategy) where shorter MAs produced the greatest returns. Other funds that show consistent and strong uptrends, such as XLK (150/350-day MA crossover strategy) and XLY (150/350-day MA crossover strategy) returned greater profits when longer MAs were used. This is supported by Table 13 below.

The results also show how using MA strategies for market prices that are bullish and consistent with little fluctuations, such as XLK and XLV, are more effective and almost as profitable as the buy-and-hold strategy. For funds with longer periods of consolidation and frequently fluctuating prices, like XLB and XLU, regardless of the MA lengths, these TFS return much lower profits than the buy-and-hold strategy. This is in line with past studies where they found that greater volatility in market prices leads to lower profitability of TFS (Fong et al., 2011). Therefore, this highlights how TFS, especially MA strategies, are more profitable when applied to stocks where prices follow a consistent pattern instead of one that fluctuates.

Table 13. Figures of Closing Prices for XLF, XLI, XLB, XLU, XLK, XLY, XLV and XLP Funds

FUNDS WITH GREATER VOLATILITY	FUNDS WITH CONSISTENT TRENDS
XLF 	XLK 
XLI 	XLY 
XLB 	XLV 
XLU 	XLP 

Conclusion

In summary, the XLK and XLY funds, corresponding to the technology and discretionary sectors, are the most profitable when using TFS. They both exhibit bullish and consistent trends which are conducive for such strategies using longer MAs. When trading with funds from other sectors that show larger and more frequent fluctuations, shorter MAs are more effective and MA strategies become much less profitable compared to the buy-and-hold strategy. Thus, this shows how TFS are truly more effective for stock prices with strong and consistent trends and there is a need to find other more profitable strategies for stocks that have longer periods of consolidation.

Different Time Periods

Market prices often exhibit varying price patterns over different time periods. With the increasing volatility of prices today, price movements have become more unpredictable. Therefore, it is essential to investigate if well-established TFS, like MA strategies, are still profitable in today's market climate.

Past Research

A study that analysed the effectiveness of TFS across 67 global markets since 1880, for each decade over the entire time period, showed how TFS have performed rather consistently despite many financial crises and major fluctuations. However, the profitability of these strategies were the highest in the 1970s and 1980s and has since deteriorated. These strategies were largely profitable when prices displayed trends that could be followed and thus, they were the most effective when stock prices showed either extremely bullish or bearish trends. This is even so during global financial crises unless the price movements are extremely sharp such that TFS are unable to shift their trading positions quickly enough. Results also illustrated how the strategy's performance has been rather consistent regardless of the volatility of market prices and the economic environment (Hurst et al., 2017).

Results and Discussion

This study analysed the profitability of MA strategies for 5-year periods over the time span of 1 January 1997 to 31 December 2021 so as to investigate if TFS are indeed still effective today and how the varying financial climates over the years will influence their profitabilities.

Table 14. Results for MA Strategies for Time Periods 1997 to 2001 and 2002 to 2006

1997 TO 2001					**2002 TO 2006**				
Buy-and-Hold	**Single MA**		**MA Crossover**		**Buy-and-Hold**	**Single MA**		**MA Crossover**	
Profits ($)	MA Length (Days)	Profits ($)	Fast / Slow MA Length (Days)	Profits ($)	Profits ($)	MA Length (Days)	Profits ($)	Fast / Slow MA Length (Days)	Profits ($)
40.27	**10**	-18.44	**25/50**	-4.02	26.09	**10**	-3.63	**25/50**	16.49
	25	-22.07	**25/100**	10.72		**25**	27.23	**25/100**	11.45
	50	-6.73	**50/100**	18.38		**50**	14.38	**50/100**	16.09
	100	-22.31	**50/150**	30.78		**100**	19.15	**50/150**	20.52
	150	10.91	**50/200**	51.06		**150**	16.15	**50/200**	34.54
	200	18.27	**100/250**	58.19		**200**	28.82	**100/250**	37.95
	250	28.16	**100/300**	56.94		**250**	26.82	**100/300**	41.11
	300	42.06	**100/350**	54.78		**300**	21.58	**100/350**	45.20
	350	42.70	**100/400**	55.81		**350**	39.16	**100/400**	41.69
	400	57.38	**150/300**	56.16		**400**	37.81	**150/300**	43.11
	450	56.25	**150/350**	61.36		**450**	33.84	**150/350**	38.62

Table 15. Results for MA Strategies for Time Periods 2007 to 2011 and 2012 to 2016

2007 TO 2011					**2012 TO 2016**				
Buy-and-Hold	**Single MA**		**MA Crossover**		**Buy-and-Hold**	**Single MA**		**MA Crossover**	
Profits ($)	MA Length (Days)	Profits ($)	Fast / Slow MA Length (Days)	Profits ($)	Profits ($)	MA Length (Days)	Profits ($)	Fast / Slow MA Length (Days)	Profits ($)
-15.87	**10**	-49.29	**25/50**	-30.89	96.03	**10**	16.80	**25/50**	29.35
	25	-38.14	**25/100**	-1.82		**25**	21.06	**25/100**	38.82
	50	-15.41	**50/100**	18.85		**50**	7.68	**50/100**	50.84
	100	4.14	**50/150**	31.86		**100**	9.02	**50/150**	52.50
	150	-9.80	**50/200**	20.05		**150**	36.53	**50/200**	70.13
	200	-6.28	**100/250**	-3.83		**200**	70.45	**100/250**	75.57
	250	-4.34	**100/300**	3.29		**250**	72.51	**100/300**	82.23
	300	-10.16	**100/350**	13.42		**300**	69.81	**100/350**	81.55
	350	-5.44	**100/400**	3.67		**350**	59.08	**100/400**	86.05
	400	-4.45	**150/300**	2.66		**400**	75.36	**150/300**	67.67
	450	-26.95	**150/350**	2.34		**450**	73.53	**150/350**	58.31

Table 16. Results for MA Strategies for Time Periods 2017 to 2021

2017 TO 2021				
Buy-and-Hold	**Single MA**		**MA Crossover**	
Profits ($)	MA Length (Days)	Profits ($)	Fast / Slow MA Length (Days)	Profits ($)
249.72	**10**	196.67	**25/50**	203.20
	25	171.32	**25/100**	142.06
	50	182.89	**50/100**	157.42
	100	169.24	**50/150**	163.53
	150	153.26	**50/200**	174.73
	200	173.42	**100/250**	171.87
	250	201.65	**100/300**	187.42
	300	192.39	**100/350**	200.24
	350	192.06	**100/400**	212.64
	400	200.00	**150/300**	236.46
	450	201.91	**150/350**	246.35

Tables 14 to 16 reveal that the efficacy of TFS vary depending on different time periods and that the buy-and-hold strategy was not always the best option.

Table 17. Figures of Closing Prices of the S&P500 Fund in 5-Year Time Periods

<table>
<tr><th>Time Periods With Consistent Trends In Both Directions</th><th>Time Periods With Frequent Fluctuations</th><th>Time Periods With Consistent Trends In One Direction</th></tr>
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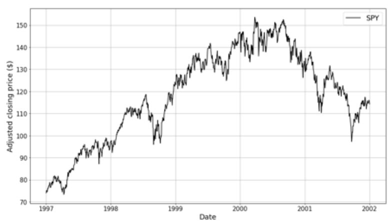
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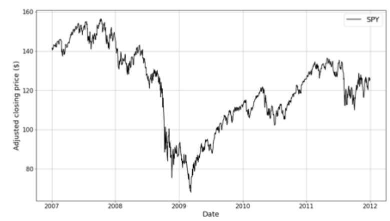
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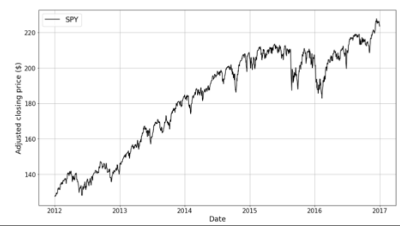
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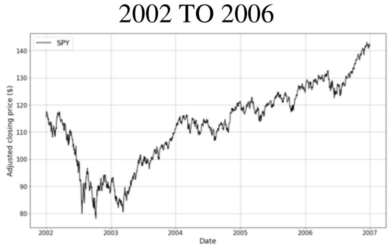
</td><td>2017 TO 2021

</td></tr>
</table>

For time periods 1997 to 2001 and 2002 to 2006, the buy-and-hold strategy was not optimal. Instead, MA strategies with longer MAs performed the best (the 150/350-day MA crossover strategy and the 100/350-day MA crossover strategy for the respective time periods). As shown in Table 17, these two time periods have price patterns displaying strong and consistent trends over long periods. From 1997 to 2001, prices displayed a strong and steady uptrend from 1997 to mid 2000 and a downtrend till end 2001. From 2002 to 2006, prices continued to fall steadily till early 2003, then rose consistently to the end of 2006. Therefore, given their consistent trends where prices were either extremely bullish or bearish, MA strategies returned greater profits than the buy-and-hold strategy and performed well. The buy-and-hold strategy was not as profitable due to the strong downtrend in each time period.

From 2007 to 2011, the fund underwent a period of consolidation as prices fluctuated repeatedly. The buy-and-hold strategy was not profitable as the prices followed an overall downtrend. Given the rapid price movements in this time period, the optimal TFS was the 50/150-day MA crossover strategy which uses shorter MAs, so as to shift trading positions more swiftly.

For time periods 2012 to 2016 and 2017 to 2021, the buy-and-hold strategy returned the greatest profits as stock prices displayed strong and consistent uptrends. Longer MAs performed better as well due to the steady increase in stock prices with little fluctuations, where the 100/400-day and 150/350-day MA crossover strategy were the most profitable TFS for time periods 2012 to 2016 and 2017 to 2021 respectively.

Conclusion

The diverse patterns and movements shown by market prices in different time periods and financial climates have a significant impact on the profitability of TFS. This study has revealed that these strategies are most effective when stock prices show either extremely strong and consistent uptrends or downtrends. This is contrary to past research that explained how the performance of TFS remain fairly consistent despite varying degrees of volatility and economic environments (Hurst et al., 2017).

Indeed, the efficacy of these strategies have declined when compared to the passive buy-and-hold strategy but this might only be the case of the S&P500 fund. The fund's strong and consistent uptrends in recent years have undermined the necessity of TFS as compared to in the past where prices also observed downtrends regularly. Should market prices display both consistent downtrends and uptrends, it is highly likely that TFS will outperform the buy-and-hold strategy. The relevance of TFS in the case of the S&P500 fund might have diminished but whether it is still profitable in other markets and for other stocks will require further research.

Conclusion

This study has investigated the performance of several popular TFS with regards to the S&P500 fund. The consistent and strong uptrends in prices have led to longer term strategies performing better, with the passive buy-and-hold strategy being the most profitable followed by strategies that used longer MAs and breakout lengths.

Strategies using EMAs gave an earlier entry signal and hence was able to reap more profits than those using SMAs. However, it was discovered that trading less frequently such as weekly or monthly actually performed better than daily trading. Stop losses were found to be largely ineffective when used in conjunction with TFS.

Using TFS in different market sectors and time periods served to investigate the efficacy of these techniques in diverse economic climates where prices exhibit distinct patterns. Our results echo many other studies where TFS are highly profitable in markets where prices show steady and strong trends instead of those where prices are volatile and fluctuate frequently. The effectiveness of such strategies are found to be diminishing when compared to the buy-and-hold strategy in the case of the S&P500 fund where prices are continuously bullish. This illustrated how TFS might be becoming less relevant in markets where prices only trend in one direction.

Ultimately, this research provides insights into TFS with respect to the S&P500 fund, especially in recent years. While it attempts to evaluate the profitability of such strategies in markets with varying price patterns, findings obtained over different funds and time periods may result in a different conclusion. This study does not aim to constrain research in this field but only hopes to emphasise the perpetual need for more. It is vital to frequently revisit this issue as the relevance and profitability of these strategies are constantly changing.

In recent times, many researchers and academics have modified certain TFS and combined them with other popular techniques to arrive at even more profitable ones. The effectiveness of an adapted TFS using trend recalling, where strategies that were profitable for price movements in similar past trends were used when current matching trends or market cycles are identified, was investigated (Fong et al., 2012). Both trend following and momentum strategies have been combined to achieve the higher return levels with much reduced volatility and drawdowns (Clare et al., 2016).

These are some successful examples of innovating new strategies and with the rapid advancements in computational powers and the proliferation of new trading indicators and rules, these increased capabilities should be harnessed to formulate more novel strategies in the near future.

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