Technical Trading ETFs in the 21st Century

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This paper tested the effectiveness of the popular trading rule based on the 50-day and 200-day moving averages on two ETFs: QQQ and SPY using daily and weekly data. We find that for both weekly and daily data, the trading rule shows good results for the entire sample. When we introduce subperiods by decades, we find that the technical rules only work around 50% of the time. When we explored the performance on shorter subperiods of 2.5 years, we found a strong correlation between realized volatility (standard deviation of returns) and the performance of active strategies. To take advantage of this correlation, we modified the basic moving average strategy so we will be invested in the asset when volatility is low but will employ the MA trading rule when volatility increases. We find that the performance of active strategies improved when volatility is considered. Overall evidence in this paper supports the continued usage of technical analysis as a protective tool for high volatility periods.

Keywords: technical analysis, moving averages, Golden cross, Death cross, VIX, QQQ, SPY

INTRODUCTION

Technical Analysis (TA) includes a broad range of trading rules based on past prices and volume to predict stock prices. The trend is one of the most important concepts in technical analysis, as Pring (1991, p. 3) points out "the art of technical analysis, for it is an art, is to identify a trend reversal at a relatively early stage and ride on that trend until the weight of evidence shows or proves that the trend has reversed". A technician can use various indicators that are based on past prices and volumes to determine the change in trend and predict future prices. Many academicians are skeptical about the use of TA and mostly believe in the efficient market hypothesis (EMH) which states that security prices always fully reflect all available information; any new information will be quickly and instantaneously reflected in a security price, Fama (1970). Furthermore, since news on any company, by definition, is unpredictable (arrives randomly), price changes will follow a random walk.

The *EMH* does not state that prices are always right but suggests that security prices could be overvalued or undervalued but no one knows whether deviations from the current stock price are up or down, they are random. Thus, there is an equal chance that stocks are undervalued or overvalued at any point in time, and this random deviation from the current price implies no one can consistently make abnormal profits, Malkiel (1973). By the end of the 1970s, almost all academicians believed that the EMH was indeed the great triumph of twentieth-century economics, Shleifer (2000). Much early research supported the EMH, an example would be Fama (1965). The implication of the EMH is that investors are better off for the long term if they buy a well-diversified portfolio, like a total stock market index. This is called buy and hold strategy, (B&H) and it is the benchmark that technical analysts try to beat. Using data for this century, this paper tests widely popular technical indicators in two ETFs and finds that technical analysis can outperform B&H strategy for periods of high volatility and develops a strategy that can provide significant benefits to investors.

LIMITED LITERATURE REVIEW OF TECHNICAL ANALYSIS

Technical trading literature can be divided into two periods, the early period (1950-1975) and the recent period (1975-present). During the early period, literature was limited and mostly was related to negating the weak form of the Efficient Market Hypothesis. For example, Larson (1960), Osborne (1962), Alexander (1964), Granger and Morgenstern (1963) all had shown that technical rules cannot have predictive power. The conclusion was that stock markets are weak-form efficient. By the early 1975s, it was established that it was not possible to outperform the market using technical trading rules.

However, since the 1980s, technical analysis (TA) has been enjoying a renaissance in academic circles. A few seminal papers presented evidence that TA is useful for predicting stock market returns. The cornerstone of this research is based on articles by Sweeney (1986), Lukac et al. (1988), and Brock et al. (1992). They all show predictive power of TA. Since the publications of the above articles, a myriad of research has appeared on the profitability of TA. Park & Irwin (2007) provide an early survey of the technical analysis literature up to 2004. In a more recent survey of the literature, Nazario *et al.* (2017) summarize and systematize the significant research that has contributed to the development of TA. Metghalchi *et al.* (2019) applied four popular trading rules to the Bulgarian Stock Index from 2003 to 2018 and concluded that moving average rules are still profitable even considering risk and transaction costs. Metghalchi *et al.* (2021) showed that TA work for small stocks but not large stocks in South Africa. In addition, in recent years, the EMH has been criticized by behavioral finance advocates who criticize the EMH assumption that investors are rational who can accurately value stock prices. Valcanoverm et al.'s (2020) provides a survey of behavioral finance. In summary, after more than half a century of research and thousands of journal articles, financial economists have not yet reached a consensus about the profitability of TA. In this paper we employ popular technical trading rules and strategies for QQQ and SPY and show that TA has predictive power and can be used in profitable trading. Furthermore, this study explores and finds when TA can be profitable.

DATA AND METHODOLOGY

We perform a simple technical trading rule for QQQ and SPY. QQQ is an Exchange Traded Fund (ETF) that tracks the investment results of the Nasdaq-100 index including 100 of the largest international and domestic companies listed on the NASDAQ stock exchange. SPY is the ETF that tracks the performance of the S&P 500 index. One common criticism for previous technical trading studies is that researchers use stock indices, which are not tradable per se and ignore dividends. The two ETFs selected in this study are extremely liquid and they pay dividends, so we can avoid these two methodology issues.

All data for the ETFs used in this paper are from Yahoo!Finance. This website provides two series of prices, the close price and the adjusted close. Both numbers are adjusted by stock splits and the difference between them is the adjustment of dividends. While the regular close price is the split adjusted price that is observed in the market, the adjusted close is an artificial series (not observed in real life) that removes the dividends paid by the stock going back in time. Adjusted prices are used to calculate the total return of the instrument (capital gain + dividend yield), while regular closing prices are used to calculate technical indicators and determine positions.

To measure the usefulness of the trading strategies we compare the annual return and annual risk of each ETF, assuming buying and holding them (Buy and Hold strategy, B&H) with the risk and return of our proposed technical trading rule and strategies for QQQ, and SPY. We use both daily and weekly historical close prices from the inception of QQQ until the end of June 2022. The choice of our trading rule is based on the popularity of these trading rules or mechanisms, as described in Metghalchi and Lopez-Garcia (2022) The terms "Golden Cross" and "Death Cross" are defined as the crossing of two major moving averages, the 50-day moving average and the 200-day moving average. Golden cross is the term used when a bullish trend starts as the 50-day MA goes above the 200-day MA. The Death Cross is referred as the start of a bearish trend as the 50-day MA closes below the 200-day MA.

For daily data, if MA50 days > MA200 days, then the rule dictates to be invested in the market, otherwise to be out of the market.

For weekly data we propose the same rule but divided by five, which is the number of trading days in a week. That way we come up with 10 and 40 weeks, which are equivalent in time to 50 and 200 days. So, the weekly strategy is stated as if MA10 week > MA40 week, then we must be invested in the market, otherwise, out of the market

In our calculations we estimate the weekly and daily returns, R_t, of each ETF by:

$$R_t = \text{Ln}\ (P_t / P_{t-1}) \tag{1}$$

where P_t and P_{t-1} are the *adjusted* closing price of each ETF in periods t and t-1. Yahoo!Finance adjusts for dividends and stock splits therefore the returns include dividend yields and not just capital gains as studies that only use price levels of the S&P index. So, the use of ETFs allows us to circumvent the bias affecting studies that ignore dividends when calculating stock returns.

Estimation of annual average return from daily and weekly returns can be done using the next equations.

$$\text{Annual Average return} = \text{Exponential (Average daily mean} * 252) -1. \tag{2}$$

$$\text{Annual Average return} = \text{Exponential (Average weekly mean} * 52) -1. \tag{3}$$

Equation 2 and 3 use geometric compounding of daily and weekly returns and 252 is the average number of trading days in the years in the sample.

We estimate the annual standard deviation (SD) of the daily and weekly returns as follows:

$$\text{Annual SD} = \text{Daily SD} * \text{Square root of } 252 \tag{4}$$

$$\text{Annual SD} = \text{Weekly SD} * \text{Square root of } 52 \tag{5}$$

And the Sharpe ratio is calculated as

$$SR = (\text{Avg portfolio} – \text{Avg } R_{rf}) / \text{SD portfolio} \tag{6}$$

where R_{rf} is the return of the risk-free instrument.

The profitability of technical trading rules depends on what a trader does when the rule issues a "BUY" order and what he/she does when the rule emits SELL signals. There are many combinations that include the use of leverage and the choice of either shorting the market or parking the money in a risk-free instrument. Following Metghalchi et al (2015), we consider four strategies: (1) the trader will be in the ETF (QQQ or SPY) when trading rules emit buy signals and will be in the money market when it emits sell signals (long/money). We use the Federal fund rate as a proxy for money market rate. In strategy (2) the trader will be in the ETF when trading rules emit buy signals and short the ETF when it emits sell signals (long/short), in strategy (3) the trader will borrow at the money market rate and double the ETF investment when trading rules emit buy signals and will be in the money market when it emits sell signals (leverage/money). The total trading return on buy days of this strategy is $TR_t = 2 * R_t – M_t$, where R_t is the ETF return on day t and M_t is the money market return on day t, and for strategy 4, the trader will borrow at the money market rate and double the ETF investment when trading rules emit buy signals and short the ETF if it emits sell signals (leverage/short).

When we compare results of active strategies against the B&H strategy, four possibilities exist as illustrated in Figure 1. Active strategies could have 1) higher return and lower risk than B&H; 2) lower return and lower risk than B&H; 3) lower return and higher risk than B&H and 4) higher return and higher risk than B&H. If you get (1), it is clear that the active strategy is beneficial to investors. This result is often referred to as the "Holy Grail" in trading. Highly sought after but hardly found. If you get (3), it is a clear failure, active trading is a waste of time and resources. However, the case for (2) and (4) is not clear cut because of time exposure and use of leverage.

FIGURE 1
POSSIBLE OUTCOMES OF A TRADING STRATEGY

$Ret_{B\&H}$

$\sigma_{B\&H} - \sigma_{Active\ Strategy}$

(2) Lower return + Lower risk "More Conservative than B&H"	(1) Higher return + Lower risk "Holy Grail"
(3) Lower return + Higher risk "Complete failure"	(4) Higher return + Higher risk "More aggressive than B&H"

$\sigma_{B\&H}$

$Ret_{Active\ Strategy} - Ret_{B\&H}$

With active trading, the time exposed to the market will be lower than 100%, which will normally reduce the risk of the active strategy relative to the passive B&H strategy and because of a lower exposure, you may end up with lower returns. With leverage, we can increase risk and if trading rule works, returns also increase. So, in order to judge if a case (2) lower return – lower risk or a case (4) higher return- higher risk is an improvement or not beyond the original B&H base case, we need to use a measure that combines risk and return. Following previous studies including Sullivan et al (2002), we use the Sharpe ratio, as defined in equation (6), to judge any results falling in quadrants (2) and (4). Since the Sharpe ratio gives you the units of excess return per unit of risk taken, preference will be given to the active strategy that produces the highest ratio above the B&H value.

EMPIRICAL FINDINGS

Daily Data

Table 1 shows the results of our MA trading rule for various strategies using daily data. For daily data, a buy signal is emitted when the simple MA50 is above than the simple MA200, if so, we buy each ETF in strategies 1 and 2 and double the investment in strategies 3 and 4. If MA50 <= MA200, we will be out of the market and in money market instrument in strategies 1 and 3 and will short the ETF in strategies 2 and 4. The QQQ series started on 3/8/1999, however, since estimating a moving average for 200 days requires previous data, all return estimations are made from 1/3/2000 to 6/30/2022. Even though SPY ETF started earlier, and we could calculate results for a longer period, to make comparison easier, we have limited the analysis to the same period used for QQQ.

As we can see from Table 1, our daily trading rule of MA50>MA200 for QQQ will result in an annual return of more than 10% with a risk of 18.6% for strategy 1, and comparing these numbers with the B&H

strategy for QQQ with an annual average of 5.8% and an SD of 27.6%, we can conclude that the MA trading rule with strategy 1 clearly outperforms B&H and a risk that is 30% lower than the risk of B&H. Trading with strategy 2 has an annual average around 14%, more than 8% higher than the B&H return for QQQ, and similar risk as the B&H strategy. Trading with strategy 1 is suitable for low-risk tolerance investors while strategy 2 is appropriate for medium-risk tolerance investors.

Trading with strategies 3 and 4 are suitable for high-risk tolerance investors with very high annual average returns, 20% to 23.8% with higher risk than the B&H strategy. We conclude that our trading rule with various strategies outperforms the B&H strategy if daily data are used for trading. Daily trading for QQQ requires 32 trades over the entire 22.5 years, or 1.42 trades per year and the percentage of time that we are "long" the market is 86%. Sharpe ratio in this case shows that any of the strategies outperforms the B&H and the apparent winner is strategy 4.

TABLE 1
RISK-RETURN FOR TRADING STRATEGIES BASED ON MA RULES USING DAILY DATA

a) QQQ		Trading Rule: MA50>MA200, 1/3/00-6/30/22 # trades =32, Time in long strategies = 86%			
	Buy & Hold	Strategy 1	Strategy 2	Strategy 3	Strategy 4
Daily Average	0.02 %	0.04%	0.05%	0.07%	0.08%
Daily SD	1.74 %	1.18%	1.74%	2.36%	2.69%
Annual Return	5.8%	10.4%	13.9%	20.0%	23.8%
Annual SD	27.6 %	18.8%	27.6%	37.5%	42.6%
Sharpe ratio	0.153	0.470	0.445	0.490	0.520
b) SPY		Trading Rule: MA50>MA200, 1/3/00-6/30/22 # trades =22, Time in long strategies = 70%			
	Buy & Hold	Strategy 1	Strategy 2	Strategy 3	Strategy 4
Daily Average	0.02 %	0.03%	0.03%	0.05%	0.05%
Daily SD	1.25 %	0.83%	1.25%	1.66%	1.90%
Annual Return	6.3%	7.5%	7.6%	13.7%	13.8%
Annual SD	19.8 %	13.2%	19.8%	26.4%	30.2%
Sharpe ratio	0.235	0.444	0.302	0.457	0.403

Note: SD stands for Standard Deviation, Annual Return is based on daily geometric compounding.

Panel b) in Table 1 shows the results of our trading rule with various strategies for daily data for SPY. Following this MA50>MA200 day trading rule with strategy 1 will result in an annual average return for SPY of 7.5% and an SD of 13.2%. Compared to B&H for SPY, trading with strategy 1 has a higher annual return and lower risk, clearly outperforming B&H. Trading with strategy 2 has about 1.3% higher average return and similar risk than the B&H for SPY, also outperforming B&H. Trading with strategies 3 and 4 produce higher returns but with higher risk. Daily trading for SPY used 22 trades over the entire 22.5 years, or 0.98 trades per year. According to Sharpe ratio, strategy 3 is the best option to use, with strategy 1 a close second. It is important to note that the leverage in strategy 3 worked well for both ETFs over this sample period.

Weekly Data

Table 2 shows the weekly results of the MA10>MA40 rule using the four strategies mentioned above for QQQ and SPY.

As can be seen from Table 2, following strategy 1 results in a weekly average return of 0.18% and a weekly SD of 2.40%. Following equation (5), we will get the annual SD of this trading rule with strategy 1 to be 17.3%. This should be compared to the annual SD of B&H for QQQ of 25.1%. Our trading rule with strategy 1 has a much lower risk than the B&H strategy for QQQ. The annual average of our trading rule with strategy 1 is, 9.7% and should be compared with the B&H average return of 5.8%. We conclude that our trading rule with strategy 1 has a higher average return and much lower risk than buying and holding QQQ.

A trader following our trading rules with strategy 2, will be in the market (Buy QQQ) if the MA10 weeks is greater than MA40 weeks, otherwise, the trader will short QQQ (Long/Short). As can be seen from Table 2, strategy 2 will result in an annual average return of 12.3% with an annual risk of 25.1%, Strategy 2 has 6.5% higher annual average than the B&H for QQQ and similar risk as the B&H for QQQ, 25.1%. Applying strategy 3, if MA10 weeks>MA40 weeks, a trader will borrow at the money market rate and double investment in QQQ, if MA10 <= MA40, then the trader parks the fund in the money market (Leverage/MM). Trading with strategy 3 for QQQ will result in an annual average return of 18.4% with a risk of 34.6%. Strategy 3 results in an annual average return of more than twice the return of buying and holding QQQ, however the risk is about 38% higher than buying and holding QQQ. Trading with strategy 4 will result in the highest annual average return, however, with a risk 55% higher than the B&H for QQQ. From the Sharpe ratios in panel a) in Table 2, we can see that a trader following strategy 1 has the best return-to-risk relation. However, if the trader had more risk tolerance, then strategies 2, 3 or 4 would have produced very good returns.

TABLE 2
RISK-RETURN FOR TRADING STRATEGIES BASED ON MA RULES USING WEEKLY DATA

a) QQQ		Trading Rule: MA10>MA40, 1/3/00-6/30/22 # trades = 36, Time in long strategies = 71%			
	Buy & Hold	Strategy 1	Strategy 2	Strategy 3	Strategy 4
Weekly Average	0.11 %	0.18%	0.22%	0.32%	0.37%
Weekly SD	3.48 %	2.40%	3.48%	4.79%	5.41%
Annual Return	5.8%	9.7%	12.3%	18.4%	21.2%
Annual SD	25.1 %	17.3%	25.1%	34.6%	39.0%
Sharpe ratio	0.231	0.560	0.490	0.531	0.542
b) SPY		Trading Rule: MA10>MA40, 1/3/00-6/30/22 # trades = 24, Time in long strategies = 71%			
	Buy & Hold	Strategy 1	Strategy 2	Strategy 3	Strategy 4
Weekly Average	0.12 %	0.12%	0.11%	0.21%	0.19%
Weekly SD	2.54 %	1.73%	2.54%	3.45%	3.93%
Annual Return	6.2%	6.5%	5.6%	11.6%	10.7%
Annual SD	18.3 %	12.4%	18.3%	24.9%	28.3%
Sharpe ratio	0.252	0.390	0.218	0.399	0.319

Note: SD stands for Standard Deviation, and Annual Return is based on weekly geometric compounding.

Panel b) in Table 2 has the results for SPY. We can see that a trader trading with strategy 1 for SPY would have an annual average return of 6.5% which should be compared to buying and holding SPY with an annual average return of 6.2%. This result is only 0.3% higher than the B&H strategy, but looking at the risk, strategy 1 for SPY had an annual SD of 12.4% which when compared with the risk of B&H for SPY, or 18.3% yields a Sharpe ratio 0f 0.390 that is much higher than B&H had (0.252).

Trading with strategy 2 for SPY will have an annual average return of 5.6% with an SD of 18.3%, so strategy 2 underperformed the B&H with a lower Sharpe ratio of 0.218. Trading with strategy 3 had a 11.6% annual average return and 24.9% SD, thus, strategy 3 produces almost 5.0% extra return with only 36% more risk than the B&H strategy. A similar conclusion can be made for strategy 4. Traders specializing in SPY have a variety of choices like QQQ, they can choose strategy 1 with lower risk than the B&H for SPY and make slightly higher return than the B&H, or choose strategies 3 or 4, with higher Sharpe ratios than the B&H for SPY.

For the entire period of 22.5 years, our simple trading rule has worked very well for both QQQ and SPY. Trading with various strategies will provide higher risk-adjusted performance than the B&H for each ETF.

In the above-proposed trading rules, a trader must look at buy and sell signals each week for weekly data (Or day, for daily data). let's say a trader looks at the price level of QQQ on Friday of each week (Or at the end of each day), a few minutes before Friday's closing price (Or each day's closing price), this trader can estimate the QQQ price level that will trigger a buy or sell signal and place a conditional limit order at the calculated trigger price. Tables 1 and 2 results assume that all trades are made at the close of the day (or week). If for some reason, the trader cannot estimate this trigger price at the end of the day (or week), the trader can initiate the buy/sell order the following day or week when the market opens; placing the order at the opening of the next day would not change our results. In both situations, we eliminate the non-synchronicity bias.

Note that in Tables 1 and 2 the annual returns estimations do not consider the transaction costs associated with getting in and out of the market. The reason is that many brokerage houses recently have adopted a policy of zero commission for the ETFs used in this paper. However, even if we consider 0.1% one-way transaction costs, this will not change our conclusion since total number of in and out trades for QQQ were 32 (daily data) or 36 (weekly data) over the entire period resulting in an annual average trade of 1.4 to 1.6 times and the effect on the annual average will be negligible. For SPY weekly data, the number of in and out trades were lower, 22 (daily) or 24 (weekly), resulting in 1 to 1.1 average trades per year, thus, even if there were trading costs, the trading rule analyzed in this paper would still work.

Evidence so far suggests our trading rules, whether applying them on weekly or daily data performs much better than the buy and hold strategy for each ETF. An interesting question is whether daily monitoring/trading produces better results than weekly monitoring/trading. We could assume that if market turns occur during a weekday, such changes could be identified earlier using daily data, which would allow for faster adjustment of positions to take advantage of the newly identified trends. That expectation works well for both ETFs studied in this paper. Active trading using daily data produces higher returns than trading based on weekly data. The gains for QQQ are 0.7% for strategy 1, 1.6% for strategies 2 and 3 and 2.6% for strategy 4 and the gains of more active trading for SPY were 1% for strategy 1, 2% for strategy 2, 2.1% and 3.1% for strategies 3 and 4.

Subperiod Results

So far, considering 2 ETFs, 4 strategies and daily or weekly data we have shown that in 15 cases out of the 16 possible combinations, the technical trading rules have produced higher Sharpe ratios in 15 cases. The only combination that failed to produce a higher Sharpe ratio than the corresponding B&H strategy occurred for SPY, with weekly data and strategy 2. That evidence would normally provide great support to the idea that technical analysis is useful and that the market is not as efficient as it is expected to be.

However, most finance professors do not believe in the predictive power of technical analysis, so we need to test how our conclusions so far hold under a series of robustness tests. One of the strongest criticisms against technical analysis is related to data snooping which argues that extended data manipulation increases the chance of obtaining the desired relationship between variables if a researcher can create 1000 different indicators and use a combination of these indicators to obtain the desired outcome. In another word, if you torture the data long enough, you could find anything you desire. One method to check that the results are robust and not came from data snooping is to use sub-samples in which the data are diced and use a different portion of the sample as validation of trading rules. (See, Andrikopoulos et al, 2008, Wasserman and Roeder, 2009, and Arlot and Celisse, 2010). Following their recommendations, we divide the entire sample into three sub-samples. If the results in each sub-sample are like the results over the entire period, then we can conclude that our findings are strong, and our results are not the result of data snooping.

Given that the tests of our strategies start the first trading day of the 21st century, we decided to split our sample into decades. We do this instead of two or three subperiods with equal but arbitrary length. We consider this approach to be a clear method that can be easily replicated by others. Our first period, the "2000s", starts 1/3/2000 and ends 12/31/2009. The second period, the "2010s" starts 1/4/2010 and ends 12/31/2019 and the third period starts 1/2/2020 and ends 6/30/2022. This gives us two 10-year subperiods and one 2.5-year subperiod.

Results for QQQ are shown in Table 3. Looking at the daily strategies, we find that in two out of the three subperiods the Sharpe ratio of the trading strategies exceeded those of the B&H. However, for the 2010s sub period, B&H performs better than any of the strategies. The results are similar when we look at results for weekly strategies.

TABLE 3
RISK-RETURN OF TECHNICAL TRADING QQQ FOR THREE SUB-PERIODS

	Buy & Hold	Strategy 1	Strategy 2	Strategy 3	Strategy 4
		Daily data, 2000s, # trades=15, Time in market = 54%			
Annual Return	-6.4%	6.1%	17.4%	9.3%	20.9%
Annual SD	34.5%	19.6%	34.5%	39.2%	48.4%
Sharpe ratio	-0.273	0.158	0.418	0.160	0.370
		Daily data, 2010s, # trades=14, Time in market = 86%			
Annual Return	17.9%	12.8%	7.7%	26.4%	20.7%
Annual SD	17.3%	15.3%	17.3%	30.6%	31.6%
Sharpe ratio	0.998	0.795	0.409	0.843	0.635
		Daily data, 2020s, # trades=3, Time in market = 84%			
Annual Return	12.6%	19.4%	26.3%	42.1%	50.4%
Annual SD	29.8%	26.4%	29.8%	52.8%	54.6%
Sharpe ratio	0.413	0.723	0.874	0.792	0.918
		Weekly data, 2000s, # trades=19, Time in market = 54%			
Annual Return	-6.4%	4.4%	13.5%	5.8%	15.1%
Annual SD	31.3%	18.6%	31.2%	37.2%	44.8%
Sharpe ratio	-0.204	0.237	0.432	0.157	0.336
		Weekly data, 2010s, # trades=14, Time in market = 85%			
Annual Return	17.8 %	13.1%	8.3%	27.1%	21.7%
Annual SD	16.5 %	14.2%	16.6%	28.4%	29.7%
Sharpe ratio	1.081	0.920	0.497	0.953	0.729
		Weekly data, 2020s, # trades=3, Time in market = 83%			
Annual Return	12.3%	18.3%	24.5%	39.6%	46.8%
Annual SD	25.7%	22.4%	25.6%	44.9%	46.5%
Sharpe ratio	0.477	0.816	0.956	0.882	1.007

Note: SD stands for Standard Deviation, and Annual Return is based on geometric compounding.

Table 4 shows the results for SPY for the three sub periods. Consistent with results for QQQ, trading strategies perform well in the 2000s and badly in the 2010s. However, for SPY, the trading strategies can't beat B&H during the 2020s sample. Contrary to findings for QQQ, trading strategies on SPY performed badly in the first 2.5 years of the 2020s.

TABLE 4
RISK-RETURN OF TECHNICAL TRADING SPY FOR THREE SUB-PERIODS

	Buy & Hold	Strategy 1	Strategy 2	Strategy 3	Strategy 4
		Daily data, 2000s, # trades=9, Time in market = 56%			
Annual Return	-1.0%	7.5%	14.3%	12.2%	19.3%
Annual SD	22.4%	11.2%	22.4%	22.5%	29.7%
Sharpe ratio	-0.179	0.400	0.506	0.409	0.550
		Daily data, 2010s, # trades=10, Time in market = 83%			
Annual Return	13.5%	8.3%	3.2%	16.6%	11.0%
Annual SD	14.7%	12.3%	14.7%	24.6%	25.9%
Sharpe ratio	0.872	0.624	0.173	0.648	0.402
		Daily data, 2020s, # trades=3, Time in market = 77%			
Annual Return	8.7%	4.3%	-0.1%	8.5%	3.9%
Annual SD	25.5%	21.4%	25.5%	42.8%	45.0%
Sharpe ratio	0.331	0.188	-0.015	0.192	0.081
		Weekly data, 2000s, # trades=11, Time in market = 57%			
Annual Return	-1.0%	5.7%	10.6%	8.5%	13.5%
Annual SD	20.3%	10.8%	20.2%	21.5%	27.5%
Sharpe ratio	-0.198	0.252	0.374	0.256	0.381
		Weekly data, 2010s, # trades=10, Time in market = 83%			
Annual Return	13.4%	8.2%	3.1%	16.4%	10.8%
Annual SD	13.9%	11.5%	14.0%	23.0%	24.3%
Sharpe ratio	0.920	0.662	0.174	0.687	0.420
		Weekly data, 2020s, # trades=3, Time in market = 76%			
Annual Return	8.6%	2.8%	-2.9%	5.3%	-0.5%
Annual SD	24.6%	20.2%	24.7%	40.5%	42.9%
Sharpe ratio	0.339	0.124	-0.130	0.125	-0.018

Note: SD stands for Standard Deviation, and Annual Return is based on geometric compounding.

Using 3 subperiods, 2 instruments, 4 strategies and 2 types of data, we have produced 48 observations of the performance of active strategies based on TA against the performance of a B&H strategy. From the original success rate of (15/16) using full sample periods, the success rate of TA drops to 50% (24 times that TA beats B&H/48 combinations), suggesting that the probability of success of beating the B&H strategy in a short period is the same as for a coin toss.

When Can TA Perform Better?

Overall subperiod results suggest that the effectiveness of technical strategies varies over time. It appears to work well in some periods but badly in others.

To further study the likelihood of success of a TA rule, we define 9 subperiods of 2.5 years. The first one starts on the first day of Jan 2000 and ends the last day of June 2002, the second one starts first day of July 2002 and ends in 2004 and repeat this process until the last subperiod, which starts Jan 2020 and ends in June 2022.

TABLE 5
BASIC STATISTICS FOR NINE 2.5-YEAR SUBPERIODS

		QQQ			SPY			SR avg gain	
Sample	Rf	Av ret	Stdev	SR	Av ret	Stdev	SR	QQQ	SPY
2000.1-2002.6	4.5%	-39.7%	53.1%	-0.833	-13.7%	22.3%	-0.818	1.320	0.81
2002.7-2004.12	1.3%	18.9%	27.4%	0.643	10.2%	19.1%	0.468	0.063	0.18
2005.1-2007.6	4.4%	7.7%	14.4%	0.226	11.1%	10.5%	0.641	-0.824	-0.18
2007.7-2009.12	1.8%	-1.1%	31.5%	-0.094	-9.2%	32.2%	-0.344	0.417	1.23
2010.1-2012.6	0.1%	15.5%	20.7%	0.746	10.5%	19.4%	0.534	-0.387	-0.78
2012.7-2014.12	0.1%	22.7%	13.3%	1.694	20.4%	11.3%	1.795	-0.053	0.09
2015.1-2017.6	0.4%	13.4%	15.9%	0.817	8.9%	13.2%	0.648	-0.733	-0.48
2017.7-2019.12	1.8%	20.0%	18.4%	0.989	14.3%	13.7%	0.909	-0.106	-0.33
2020.1-2022.6	0.3%	12.6%	29.8%	0.413	8.7%	25.5%	0.331	0.413	-0.22

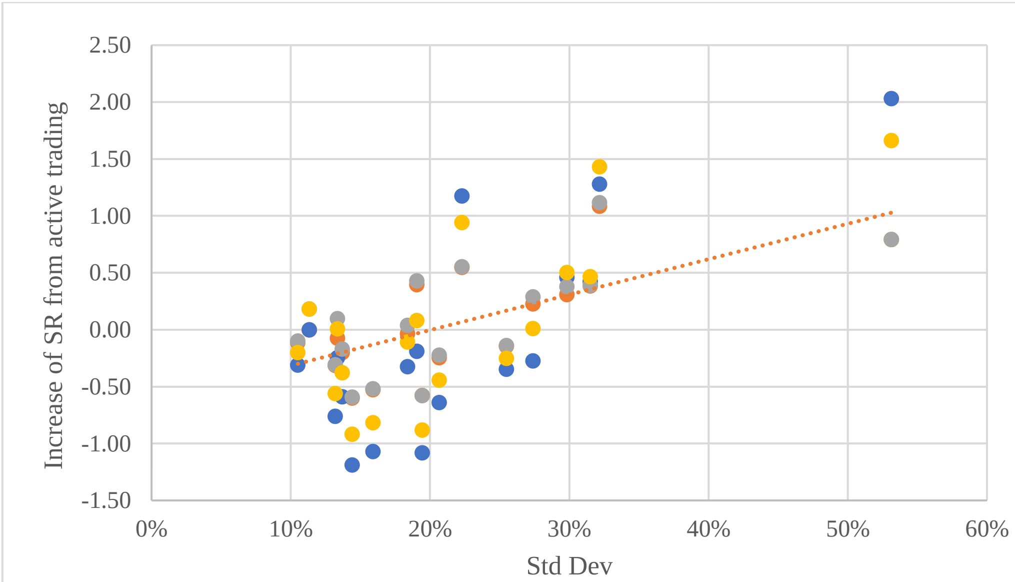
With data from those nine 2.5-year subperiods, for QQQ, we observe a higher Sharpe ratio than the B&H in 50% of the combinations (samples, strategies). However, for SPY, the success rate is only 36.1%. We consider these two estimates for the probability of success of TA to be more precise given the larger sample. Unfortunately for proponents of TA-based active strategies, results suggest that the good results shown in Tables 1 and 2 were particular to the sample used in the paper.

Nevertheless, the bad results obtained with 2.5-year subperiods raises questions as to how positive results appear good in the overall period but not in the majority of subperiods. To investigate this issue, we start with some sample statistics for the whole period and the subperiods.

The last two columns in Table 5 show that using average across strategies, active trading outperforms B&H 50% of the time. However, we can see a strong correlation between the risk of the asset and the performance gain of the trading strategy. We notice this in the first subperiod for QQQ where the asset had an extremely high risk, the active strategies performed very well but in low-risk periods (samples 3, 6 and 7) active strategies underperformed the B&H. For SPY we also observe that in the high-risk period (sample including 2008), active strategies performed very well. When we estimate the correlation between these two variables, we find 0.91 for QQQ and 0.62 for SPY, suggesting that active strategies work well when volatility is high. This high correlation is also illustrated in Figure 2, which plots the increase in Sharpe ratio for different trading strategies and subperiods.

So far, we have only used one technical analysis rule (MA50 vs MA200) and results are not very good. Despite the increase in Sharpe ratio for the full period, subperiod results indicate that results vary across time. Nevertheless, as shown in Table 5 and Figure 2, the protective nature of the MA50 – MA200 rule seems to be producing high gains in return (and Sharpe ratio) when volatility is high, which supports the idea that MA rules, used as protection strategies, work well in critical periods such as the financial crisis of 2008, the dot-com bubble burst of 2002 and/or the recent COVID pandemic.

FIGURE 2
INCREASE IN SHARPE RATIO FOR TA TRADING STRATEGIES APPLIED TO QQQ, SPY



To test this idea, we modify our initial strategy as follows:

> *In periods of low volatility stay invested in the stock market but in periods of high volatility, follow the Moving average trading rules.*

To identify high volatility periods we use the Chicago Board Options Exchange (CBOE) Volatility index known as VIX, which is available from Yahoo!Finance since 1993. We identify high volatility periods as any day (week) where the 50-day (10-week) Moving Average of the VIX is above the historical average standard deviation of large stocks. This historical average varies over time as periods of high volatility alternate periods of low volatility. Some textbooks identify the historical risk of large stocks as 15%, others say it is closer to 20%. It all depends on the sample used. The sample used in our study for SPY (large stocks) included several periods of high volatility and the average standard deviation was 22.4%. Given that "historical" risk is not easily determined or agreed upon, we explore results allowing the VIX trigger to vary between 14 and 22 percent.

Table 6 shows that Sharpe ratios improve when we turn on the protective MA strategies in periods of high volatility. The best triggers to initiate protection in our sample were 18 for the QQQ and 16 for the SPY, but benefits are obtained for any trigger between 15 and 20.

TABLE 6
SHARPE RATIOS OBTAINED BY TRADING STRATEGIES USING VIX - MA RULES

	Avg Sharpe ratio (daily)		Avg Sharpe ratio (weekly)	
	QQQ	SPY	QQQ	SPY
B&H	0.15	0.23	0.17	0.25
MA50-MA200	0.48	0.40	0.47	0.33
MA & VIX above				
14	0.52	0.40	0.51	0.34
15	0.56	0.43	0.55	0.35
16	0.59	0.45	0.55	0.40
17	0.60	0.44	0.58	0.39
18	0.61	0.43	0.59	0.40
19	0.56	0.43	0.54	0.40
20	0.48	0.40	0.46	0.39
21	0.41	0.31	0.42	0.33
22	0.41	0.36	0.38	0.33

Overall performance of the VIX-MA trading strategies shows significant improvements above the simple MA rule. While the initial MA trading rule applied on QQQ produced improvements over B&H in 50% of the combinations of samples and strategies, when the volatility trigger is introduced, the percentage of combinations with improvements in Sharpe ratio goes from to 75%. The improvement in average return of adding the VIX trigger to the simple MA rule is 4.4% (0.3%) for daily (weekly) data. These numbers are not shown in the tables but are available from authors upon request. For SPY, the improvement is less noticeable, success rate only increases to 44% (from 36%) of the combinations. Returns also go up for all trading strategies and on average, the improvement over the simple MA rule is 1.2% (0.6%) per year for daily (weekly) data.

Across both ETFs, following Strategy 1 under the VIX-MA rules, investors could outperform B&H using daily (weekly) data and produce higher Sharpe ratios. If investors allow for leverage (strategy 3), they could significantly outperform the B&H strategy. While this result is evident for long periods of time, the likelihood of success of the VIX-MA strategy over short periods favors QQQ (75%) compared to SPY (44%).

Evidence shows that the use of protective strategies is quite beneficial for investors. Not only do they reduce risk compared to the B&H strategy, but they can achieve higher returns; and for those willing to take higher risk using leverage (strategy 3), the benefits are economically significant. As expected, we find that trading daily produces higher returns and higher increases in Sharpe ratios than doing it on a weekly basis.

SUMMARY and CONCLUSIONS

This paper tested the effectiveness of the popular trading rule based on the 50-day and 200-day moving averages on two ETFs: QQQ and SPY using daily and weekly data. Given that these ETFs became available in the 1990s and our trading rules require preliminary data to calculate the parameters of the strategy, we start reporting our results from January 2000. We find that for both weekly and daily data, the trading rule shows good results for the entire sample. When we split our sample into decades, we find that the technical rules only work around 50% of the time. To further explore the period-by-period differences, we split each decade into four 2.5-year subperiods and end up with 9 periods for each instrument. While reviewing the success rate across subperiod/strategies/instruments, we found a strong correlation between realized volatility (standard deviation of returns) and the performance of active strategies. To take advantage of this correlation, we modified the basic moving average strategy so we will be invested in the asset when volatility is low but will employ the MA trading rule when volatility increases. To measure the volatility, we used the CBOE volatility index (VIX) and to separate periods of high and low volatility we tested historical values between 14 and 23. We find that for most of the values tested, the performance of active strategies improved. The trigger point that worked best for SPY was 16 and for QQQ was 18, but results were good for values in the 15-20 range. Overall evidence in this paper supports the continued usage of technical analysis as a protective tool for high volatility periods, rather than as a market timing tool. Given the trend of online brokers to offer free trades on stocks and ETFs, the excess returns should be fully captured by active traders. Even when we consider that every trade carries an implicit cost in the bid-ask spread, these two ETFs are the most liquid in the US markets and the estimated cost per trade is 0.05% or lower, and because the 50-day and 200-day moving averages produce a small number of trades, active traders get to keep most of the gains of the proposed strategy.

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