Analyzing the Impact of Filtering Trends using Momentum Technical Indicators on Bollinger Bands

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ABSTRACT

The purpose of this paper is to determine the effectiveness of Bollinger Bands in combination with momentum indicators. For the purposes of this study, an algorithm will combine Bollinger Bands with a single momentum indicator and utilize it to filter out areas where the market is trending. The research was conducted on three different momentum indicators and examined directional results. Ultimately, it was ascertained that there are high levels of correlation between the trend of the market and the success of Bollinger Bands, but this alone did not seem to account for the gap between the theoretical and experimental results. Future research should aim to bridge this gap by investigating other forms of bias in the market such as news, market sentiment, domestic and foreign policy, and socioeconomic standing.

INTRODUCTION

Stocks have historically been seen as a subset of our economy - a portionable size with limited impact. However, today, we observe that the scope of the stock market has far surpassed the economy. The U.S. stock market is valued at over 49 trillion US dollars, and continues to grow at an astounding rate (Siblis Research). The US economy, on the other hand, is valued well below half of the US stock market, at 21 trillion US dollars (World Bank). Over the last 10 years, the US stock market has grown over 200%, and continues to advance at a rapid rate (Siblis Research). This magnification of the stock market is exacerbated by the burgeoning markets in countries across the globe, the development of corporations, and the fact that the stock market is an integral part of our capitalist economy (American Institute for Economic Research).

Mathematical models for the stock market have lasted for hundreds of years. However, we've seen large developments in application due to the advent of computing technology -- which allows for data to be analyzed quantitatively at much higher speeds. Recently, a form of determining patterns has gained increasing attention for its supposed ability to predict the market: technical analysis. According to the Constitution of the Market Technician Association, technical analysis can be defined as "the study of data generated by the action of markets and by the behavior and psychology of market participants and observers. Such study is usually applied to estimating the probabilities for the future course of prices for a market, investment, or speculation by interpreting the data in the context of precedent." (CMT Association).

Studies have exhibited that today's stock market is filled with a wide prevalence of technical analysis. In fact, it was discovered that over 70% of Commodity Trading Advisors (CTAs) were classified as technical traders (Billingsley and Chance, 1996). The popularity of technical analysis is furthered by the fact that over 50% of non-professional traders rely heavily on technical analysis (Smidt, 1965). Despite the frequent usage of technical analysis, there is much debate on the actual profitability of it. Unlike its counterpart, fundamental analysis, technical analysis is often criticized for gaps in research and lack of conformity in literature.

LITERATURE REVIEW

Technical analysis of stocks has long been used as a leading method in identifying entry and exit points for stock trade. However, as mentioned previously, the profitability of technical analysis is often in question across literature. In a meta-analysis published by the Journal of Economic Surveys, it was concluded that modern literature indicates technical analysis was supported to be profitable only before the 1980s in the American Stock Market. Over 95 sources of modern literature were analyzed, but it was determined that there was not sufficient evidence pointing towards the effectiveness of technical trading post-1980s. The authors note, however, that the same principles of technical analysis "were at least profitable until the early 1990s" in the foreign exchange market (Park & Irwin, 2007).

One of the most modern and applied forms of technical analysis includes using the momentum[1] of price in order to determine a trend. Previous studies have demonstrated that the use of momentum indicators as a guide for portfolios is highly profitable. For example, Ratchata Peachavanish, a professor at Thammasat University, evaluated the Thai market and implemented momentum indicators

[1]Momentum in the stock market refers to the tendency of a stock to move in a certain direction as a result of previous movement in a direction.

in order to better optimize market portfolios. Using a simulation, Peachavanish concluded that the use of momentum indicators most likely allows for the long-term optimization against indexes in a bull market (Peachavanish, 2016). Similarly, a study conducted over the European stock exchanges examined over 8,000 companies in 15 countries. They found that using a momentum measure "enhance[d] value and growth in portfolios consisting of all European stocks," and that momentum has the potential to be deployed in individual markets and regions successfully (Bird & Casavecchia, 2007). Due to a momentum indicator's lack of ability to analyze other factors affecting a trend, it has been largely unsuccessful as a sole indicator for entry and exit points. However, momentum indicators can be applied in other methods in order to increase the effectiveness of a portfolio. Thus, research has attempted to determine an effective amalgamation of momentum and other indicators.

For example, a price momentum indicator has been tested with value indicators. A study that investigated the Finnish stock market attempted to test exactly this. The researchers first divided up pre-made portfolios into several groups by value indicators. Then, these groups were further segmented into those with high momentum and those with low levels of momentum. In this study, however, the researchers concluded that the momentum indicators had not been proven to have a significant positive impact on stock trading (Leivo, 2012). An additional study, published by the International Journal of Managerial Finance, realized similar results[2], though indicators were not combined. Instead, price and earnings momentum was used concurrently with a value portfolio (Bird & Casavecchia, 2007). However, not all research is in accordance; particularly, some studies in different markets vary. A study that looked at the RSI, MACD, and scholastic indicators in the Spanish stock exchange found that all three were profitable, but in different, significant amounts (Rosillo et al, 2012). The mutability in observed results from the mixed studies presented underscores the unique circumstances and factors applied in each study. Due to the highly variable nature of technical analysis across literature, it is often difficult to ascertain whether certain aspects such as momentum indicators have any profitability. More recently, however, through the use of artificial neural networks, studies have been able to ascertain the profitability of momentum indicators. For example, a study conducted by the International Multiconference of Engineers and Computer Scientists demonstrated that through using a Adaptive Neuro-Fuzzy Inference System (ANFIS), a type of ANN, momentum can be used for high levels of profitability. Unfortunately, due to current limits on processing and the lack of real time market data, systems such as these are not applicable in the status quo (Agrawal et al., 2010).

One of the most popular indicators of trend analysis, especially in the stock market, is Bollinger Bands. This analytical technique was created by John Bollinger in order to quantify relative high-low prices. Bollinger articulates that based on the probability distribution of a random process, the stock market should subsequently follow a similar distribution, as it is also a random process. By definition of standard deviation, an implied curve should have an equal distribution on both sides. As an inherent property of the stock market, smaller moves are more likely to occur than larger moves. This creates an ideal Bell Curve, where further deviations are much more unlikely (Bollinger, 1992).

However, Bollinger Bands have long been correlated with negative outcomes in literature. In a study conducted in 2007, the efficacy of Bollinger Bands for entry and exit points of trades were applied on different ETFs[3]. After the extrapolation of data, it was discovered that none of the results had significant outputs and were often negative. This indicated that the theoretical attempts to describe the stock market through the use of volatility by Bollinger did not hold up in an experimental setting (Lento, 2007). This very theoretical versus experimental disconnect will be addressed in this paper.

Gap in Literature. As the theoretical basis derived from Bollinger Bands is founded on the claim that the stock market is randomized and produces an ideal Bell Curve, any deviation from such could potentially lead to the inefficacy of Bollinger Bands exhibited in the Lento analysis. As exhibited by

[2]This study found similar results, but varied from [2] in one key way - they determined that momentum could be a successful indicator where "the difference in monthly performance between the 'best' and 'worst' value (growth) portfolios is 2.6 percent for holding periods of 12 months."

[3]Exchange Traded Fund

several aforementioned studies related to the momentum indicator, experimental application of momentum in the proper setting can be effective. Thus, through the application of momentum indicators to filter Bollinger Bands away from the potential bias of a trend, the randomness of the stock market should increase-- thereby warranting the use of Bollinger Bands and displaying its efficacy.

METHODOLOGY

Basic Apparatus. This study will focus on the combination of both volatility indicators and momentum indicators. Through the use of these indices, Bollinger Bands should approach the expected success rate as aforementioned. For the purposes of this study, Bollinger Bands will be analyzed in an algorithmic fashion with the various momentum indicators. First, the utilization of much historical stock data was necessary in order to create the underlying foundation for the indicators. Using a program known as TradingView, this study was able to access historical data along with an application programming interface. This allowed the use of algorithmic preconditions in each portion of the study. The algorithms were considered over a period of 21 years to strike an effective balance between the evolving stock market and the amount of time necessary to create trends. Given that each algorithm at most takes data from the previous 20 days, the 21 year period allows sufficient time to generate data points with statistical significance.

In order to remain in convention with typical stock market literature, a one-day candle interval was utilized. Furthermore, indicators employed the close price to perform calculations. The basic apparatus constructed for this experiment consisted of a two algorithm amalgamation at any point. Both algorithms would use conditions that were indicative of a “trade zone.” Whenever both conditions were met, the program would automatically short/long the underlying security. The momentum indicators consisted of ranges of trade zones, whereas the Bollinger Bands created specific entry points. Thus, the program triggered at the unique entry points of Bollinger Bands. Those points were then filtered using the momentum indicators before the placement of a trade.

Reducing Long-Term Market Bias. Over this 21 year period, there has been definitive long-term market bias. This must be considered for several reasons. First, this market bias has the potential to directly upset the success rate of each Bollinger Band. Second, it detracts from the theoretical basis of this examination. Given that this study attempts to measure the level of Bollinger Bands’ success in the relative absence of momentum and trends, this long-term bias poses a confounding threat. Third, irrespective of the current market bias, future application of this research will only be possible if the methodology accounts for long-term trends, as they are subject to change. Thus, in order to reduce bias, a simple approach was employed: the use of a bi-directional model. Each grouping in this study was split in two. The trade entry points were created with respect to both directions (in the presence of shorts and longs). By dividing the data into these subsets, long-term market bias is accounted for. If there is enough market bias causing data disfiguration, there should be a large discrepancy between the short and long win rates.

Algorithms and Modeling. Bollinger Bands were modeled using standard deviation from a 20-day smoothed, simple moving average, given by the following equations:

$$\sigma = \sqrt{\frac{\sum_{j=1}^{N} (X_j - \overline{X})^2}{N}}$$

$$\overline{X} = \frac{\sum_{j=1}^{N} X_j}{N}$$

(1)

where the upper, lower, and bottom bands could be defined as:

$$Upper\ Band = \overline{X} + 2\sigma$$
$$Middle\ Band = \overline{X}$$
$$Lower\ Band = \overline{X} - 2\sigma$$

The Bollinger Bands are thus a statistical measure that carefully utilizes volatility in order to create “bounds” in which a random process should stay. In application, three resultant series were created-- one for each band. The Bollinger Bands received a singular simple input in order to begin its calculations: the close price over the last 20 days. This was expressed as a series, with each value containing the close price and the corresponding date. Using this data, the standard deviation and the 20-day smoothed average were calculated. Both were individual series that represented their specific subset calculations. At each time interval (day), the lower and upper bands were created by adding and subtracting the standard deviation series from the 20-day smoothed moving average series. This created three series for further application in the program. In accordance with previous literature and the theoretical mission of this paper, entry points were defined as a point closed inside the Bollinger Bands directly following a close price outside the bands.

Three unique momentum indicators were modeled by the algorithm. As aforementioned, at any one given run of the algorithm, only two indicators were used: Bollinger Bands and a single momentum indicator. Thus, the program ran three iterations for every security it was performed on, one for each momentum indicator. The first momentum indicator used was the ADX. The ADX is a directional model that measures trend strength through the following calculations. First, the model begins by calculating two sub-momentum tracking indicators, The Plus Direction Indicator (+DI) and Minus Direction Indicator (-DI):

$$+DI = 100\left(\frac{Smoothed(Current\ High - Previous\ High)}{ATR}\right)$$

$$-DI = 100\left(\frac{Smoothed(Current\ Low - Previous\ Low)}{ATR}\right)$$

(2)

These two individual indicators alone could potentially track momentum, but in order to create a more effective representation of momentum, previous studies and theoretical math has shown that the combination of these indicators allow for a more complete mathematical picture. Furthermore, in order to create a stronger correlation between momentum and the mathematical equalities, literature has almost always smoothed and averaged this process, resulting in a further defined equality. This can be expressed mathematically as the following:

$$DX = \left(\frac{|Plus\ DI - Minus\ DI|}{|Plus\ DI + Minus\ DI|}\right) * 100$$

$$ADX = \frac{(Prior\ ADX * 13) + Current\ DX}{14}$$

(3)

From this, it is visually apparent that the ADX is a recursive series, as it allows for the management of less data in order to make predictions, while still taking into account the previous 14 days. Furthermore, it is also apparent that the process is non-directional and will not indicate whether a security is trending upwards or downwards. Rather, the process only demonstrates the strength of the trend. Inside the program (TradingView), the process was performed linearly. The script used the time series of close prices as inputs into the functions described above. The output was the creation of a time series of ADX values, ranging from 1 to 100. In line with conventional measures, values under 25 were considered to indicate a weak trend or a ranging market, while values above 25 were considered to be a trending market. Thus, the trade zone for both long and short trades were confined to values when the ADX was below 25 and after price action retracted back into the Bollinger Bands.

(4)

Along with mathematical expressions and algorithmic testing, graphical results were also produced for an illustrative effect. “BB-Long +1” refers to the theoretical purchase of a security at that point. The red line represents the 20 day moving average, while the green lines represent the Bollinger Bands. At this point of purchase, the price had closed below the bands and then closed inside the bands. This was the first precondition. The ADX at this point was 22, which was lower than the preset value of 25. Since both pre-conditions were met, the program executed the theoretical buy.

The second momentum indicator that was tested in tandem with the Bollinger Bands was the Relative Strength Index (RSI). This indicator, like the ADX, mathematically depicts the trend strength with an output ranging from 1 to 100. However, unlike the ADX, the RSI is directional. The RSI is often modeled through the following:

$$RSI = 100 - [\frac{100}{1 - \frac{Previous\ Average\ Gain * 13 + Current\ Gain}{Previous\ Average\ Loss * 13 + Current\ Loss}}$$

(5)

The RSI assists in the depiction of the trend both upwards and downwards. This means that the directionality of the RSI adds another factor that can be utilized for stock trading. A higher RSI indicates a strong trend upwards while a lower RSI indicates a strong trend downwards. This is unlike the ADX, where a higher number (closer to 100) indicates a stronger trend regardless of the direction. The range of the trading zone of the RSI is estimated to be from 30 to 70. Here, an RSI less than 30 would indicate a strong trend downwards, and a RSI greater than 70 would indicate a strong trend upwards. Thus, in order to properly test the hypothesis, the pre-conditions for a trade were set in this trial to an RSI between 30 and 70 and a close of the security after the price retracted back into the Bollinger Bands.

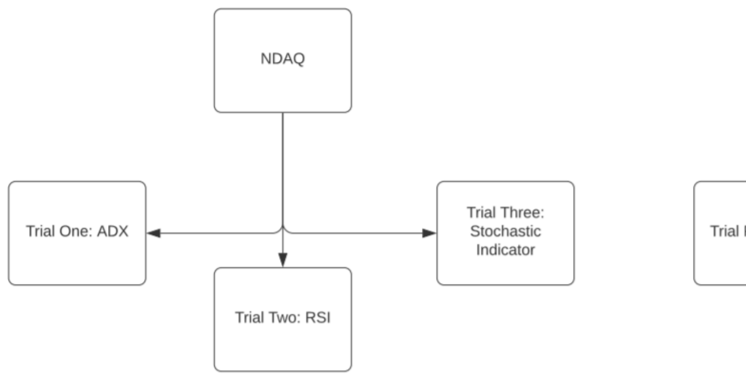
The third iteration of the test was conducted using a momentum indicator known as the Fast Stochastic Indicator. The mathematical model for the Fast Stochastic Indicator (%K) is relatively simple:

$$\%K = 100 * (\frac{Close\ Price - L14}{H14 - L14})$$

(6)

The stochastic indicator is very similar to the RSI in terms of application. It outputs a number from 1 to 100 in a bounded, continuous range. Furthermore, it is also directional in that higher numbers indicate stronger trends upwards while lower numbers indicate stronger trends downwards. In order to determine the ideal range of the market for the trade zone, mid-range values were examined. Inside the program for this research, the close price time series was used as the input for this indicator. The ranges that were determined to be in the trade zones and used for the purposes of this paper were values between 20 and 80; this is again in conformity with existing literature.

Data Exportation. Each trial was conducted over the SPY (S&P tracking ETF) and the NDAQ (NASDAQ tracking ETF). The data was divided into 12 subgroups (6 trials, each producing outputs of long and short results). The outputs of each run in consideration were then manually transported to Google Sheets. After the iterations concluded and the efficacy was recorded, z-tests were conducted in order to calculate confidence intervals.



RESULTS

Table 1. Comparing Effectiveness Between ETFs

			Statistical Analysis	
	Effectivity	Iterations	Z-Score	Confidence Level
SPY				
Long	0.7474747475	198	7.994905472	1
Short	0.6524390244	164	4.086998649	0.9999781505
Total	0.7044198895	362	8.511837848	1
NDAQ				
Long	0.6875	144	4.837354649	0.9999993421
Short	0.6358024691	162	3.580890168	0.9998287872
Total	0.660130719	306	5.904099193	0.9999999982

Table 2. Comparing Effectiveness Between Momentum Indicators

	Effectivity	Iterations	Statistical Analysis	
			Z-Score	Confidence Level
ADX				
Long	0.6976744186	129	4.869581143	0.9999994408
Short	0.6574074074	108	3.43092144	0.9996992326
Total	0.6793248945	237	5.902353241	0.9999999982
RSI				
Long	0.7283950617	162	6.515493565	1
Short	0.6373626374	182	3.843955344	0.9999394665
Total	0.6802325581	344	7.157057036	1
Stochastic				
Long	0.7647058824	51	4.412613041	0.9999948935
Short	0.6388888889	36	1.710678639	0.9564297734
Total	0.7126436782	87	4.357677689	0.9999934275

DATA ANALYSIS

Assimilating Data Collection Methods. Due to the large variety in the methods of data collection described above, statistical methods were necessary to prove significance. In order to create confidence intervals to support whether or not the sample created was significant, z-tests were applied. Z-scores were determined using the following formula:

$$z = \frac{\bar{x} - u}{\sigma/\sqrt{n}} \quad \textbf{(7)}$$

$\bar{x}$, u, σ, and n represent the sample's mean, the population's (ideal) mean, standard deviation, and sample size respectively. Over almost all cases, a greater than 99% confidence interval was observed, indicating probable correlation. It should be noted that this refers to the probability of correlation between the algorithms and the efficacy, but not the level of correlation itself.

The aforementioned Lento study demonstrated that there were close to no statistical deviations across ETFs. Thus, implied effectiveness of the population was set to 50%. In order to calculate the standard deviation, a set was constructed, using 0s as loses and 1s as wins. Thus, the efficacy was equivalent to the mean, and the standard deviation was able to be calculated. As visually apparent, each result had a high level of statistical significance. Out of the single data measures collected, only one proved to be insignificant: the Stochastic Indicator using shorts on the SPY. In regard to the level of correlation, it would seem that going long using the Stochastic indicator on the NDAQ has the highest level of efficacy, with an accuracy of over 88%.

DISCUSSION

Implications. Due to the widespread introduction of technical analysis, this research supports that there is merit in using such mathematical representations. Since this study examines a subset of the field of technical analysis, it further demonstrates that there is potential validity in the field as a whole, whereas previous research was largely inconclusive. Such predictive powers can allow for economists to accurately predict large economic moves and take proper action beforehand. When applied at a governmental level, methods of technical analysis can be utilized to determine whether policies are necessary or if the stock market is within the confines of normalcy. As aforementioned, the US economy is heavily dependent on the stock market, and further understanding of this process allows for safeguards against crashes to be better created.

Limitations. There were a few limitations in the methodology of this research. Each limitation can be improved with further research and additional resources. The first limitation is the sample size of ETFs and their corresponding scope. The two ETFs examined during the course of the study were the SPY (tracking the S&P) and the NDAQ (tracking the NASDAQ). It should be noted that both correspond to American Stock market sentiment, so similar technical analysis may produce different results across other exchanges. This is due to factors such as sentiment, market psychology, and investors. Additionally, there were several areas in which points were conformed to literature standards. However, by improving the selection of the algorithm parameters, better results could have been yielded. Furthermore, due to the constraints of computational power, this research was not applicable to smaller time frames. This includes intervals such as per second, where data could have been collected in a larger sample size. As market psychology tends to affect larger time frames with more accuracy, this research paper focused on a long period, with a day long interval. Lack of historical data further propelled this research away from low-interval timings-- much more stock data is necessary in order to create lower time frame testing. Finally, applicability of the results in the traditional sense needs further research to determine exact probabilities. While most of the data visually indicates that there are high levels of profitability, the algorithms must be further tested in order to check for asymmetries that are created as a result.

Filling Gaps in Literature. The impact of this research is two-fold in terms of advancing current literature. First, much of modern research has not been able to support the efficacy of technical analysis. As demonstrated by Park & Irwin in 2007, a meta-analysis of research in this field has proven largely inconclusive and lacks perspective about the modern market. Since this study indicates that the modern markets have a correlation with momentum and Bollinger Bands, the principles of technical analysis show the continued predictive power of technical analysis as a valid alternative to pure fundamental analysis. This proposition of change across time is especially valuable, as many have argued dynamic factors have changed technical analysis in the present era, such as the introduction of AI or the extremely widespread use of technical analysis.

When examining the impacts through a narrow scope, this paper extends off the Lento (2007) study, which states Bollinger Bands are not effective as they theoretically should have been and the numerous studies supporting the power of momentum indicators in the stock market. This research affirms that momentum plays a large role in the market, and that momentum indicators are able to accurately predict this to a statistically significant level.

Future Research. There are many avenues of future research that could extend from this study. While this research indicates with an extremely high, significant probability that momentum is a bias that affects Bollinger Bands in the market, it is visually apparent that it does not completely bridge the hypothetical gap. As initially theorized by John Bollinger, the probability should eventually approach the idealized Bell Curve, indicating that much bias still exists deviating the stock market from a completely random process. Future research should attempt to comprehend potential confounding factors such as news sentiment, market psychology of gains versus loss, and fundamental analysis itself.

As stated before, the advent of new computing technologies also allows for advanced forms of momentum analysis through the use of many parameters. Further research could also choose to examine the effectiveness of removing momentum from Bollinger Bands using a more precise set of parameters, perhaps allowing for the assertion of specific correlation levels.

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