USING BOLLINGER BANDS AND STOCHASTIC OSCILLATORS AS A TRADING STRATEGY FOR LARGE CAP STOCKS

by

Ryan Maxum

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Project Approved:

Supervising Professor: Dr. Julie Dahlquist

Department of Finance

Committee Member: Jessica Cates

Alcon Career Center

ABSTRACT

The purpose of this paper is to examine the use of technical analysis in the US equities market. Stochastic Oscillators and Bollinger Bands are both momentum metrics that use historical prices to predict the future movement of a stock price. This paper aims to prove the effectiveness of using these two metrics in a trading strategy and therefore the feasibility of exclusively using technical analysis to trade large cap equities from 2012 to 2014. The combined metrics will reduce exposure to the stock market while attempting to identify superior times to enter into positions that will exceed the average return of each equity. This paper runs additional scenarios to further understand the results and modify the combined trading strategy to improve the results and find the best use of Bollinger Bands and Stochastic Oscillators as a trading strategy for large cap stocks from 2012 to 2014.

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Introduction

A blindfolded monkey throwing darts at a page of stocks has outperformed the market by an average of 1.7% per year from 1964 to 2010. Back in 1973, Princeton Professor Burton Malkiel made the claim monkeys throwing darts could select a “portfolio that would do just as well as one carefully selected by experts” and in 2013, Arnott, Hsu, and Tindall found that the monkeys actually outperformed that market. However, fund managers are paid millions of dollars every year to pick stocks and people trust them with their money. The goal for a fund manager is to achieve superior profits over the market, or alpha, but they don’t always achieve it. Despite this, the majority of investors believe in the efficient market hypothesis (EMH), which is the belief that the stock market reflects the relevant information that may affect prices. With efficient prices, it would be impossible for investors to beat the market and achieve superior returns (Jordan, 1983). This belief would render fundamental analysis of a company useless, only resulting in the current prices. The other branch of analysis is called technical analysis. Technical analysis holds the belief that stock prices will follow repetitive patterns, which will allow for the use of past market data, primarily price and volume, to forecast the direction of prices (Jawade, Naidu & Agrawal, 2015). Believing in technical analysis to achieve alpha directly opposes the EMH.

There have been a number of studies conducted in the past that evaluate the effectiveness of technical analysis. The use of Bollinger Bands when trading in the Baltic stock market was examined and the study concluded that the bands could be used for superior returns (Kabasinskas & Macys, 2010). However, the different stock market across the world trade differently. In a study done on the Indian stock market, Nifty, used oscillators over the course of a full year to try and achieve alpha on futures (Hartono & Sulistaiwan, 2014). Another study examined Stochastic Oscillators and the appropriateness of the metric’s lower and upper limits that indicate buy and sell signals, concluding the effectiveness of the lower limit does not deviate from the defined standard of 20 but an upper limit higher than the standard 80 yields higher returns (Jawade, 2015). The study of technical analysis has also extended beyond the stock market to exchange rate trading. For exchange rates, Bollinger Bands have a weakness for financial series that have a fat tail or leptokurtic distributions. A study found that using an adjusted Bollinger band takes into account these distributions and volatility clustering and can perform much better in exchange rate trading (Chen, Chen & Chuang, 2014).

Despite this research and studies, there has not been as much work done within the US stock market over the past couple of years. US stocks behave differently than other indexes due to a number of factors, including having more traders and a stronger economy. Can the combination of Bollinger Bands and Stochastic Oscillators in a trading strategy achieve superior return when used in trading large cap US stocks? This study will use historical prices from the largest 20 stocks in the S&P index over a three year period from 2012-2014. The research aim to use the standard Bollinger Bands and Stochastic Oscillators for each security, before adjusting the variables to the agree with previous research. The analysis attempts to prove alpha can be achieved by only using technical metrics to determine periods to take a short or long position in a stock.

Introduction to Technical Analysis

Security analysis can be grouped into two broad categories: fundamental analysis and technical analysis. Fundamental analysis attempts to measure a security's intrinsic value by looking at a company's financial statements and general macroeconomic factors. Technical analysis holds the belief that stock prices will follow repetitive patterns which will allow for a predication of future prices (Jawade et al., 2015). Rather than using fundamental analysis to attempt to determine a stocks intrinsic value, technical analysis instead analyzes statistics to predict the future activity. There are three assumptions for technical analysis (Janssen, Langager & Murphy, 2015):

1. The market discounts everything
2. Prices move in trends
3. History repeats itself

Technical analysis works best when a security's price reflects all information that may affect the company which includes fundamental factors. If the stock is properly priced based on all of the available information, then it only leaves the price movement to change the price which can be viewed as supply and demand for the stock (Brown & Jennings, 1989). Additionally, technical analysts believe a stock price trends, and once the price begins a trend, its future price will be in the same direction. Finally, history repeats itself. Aligned with the first assumption, this assumes that historical price movement will repeat itself (Janssen et al., 2015). "The repetitive nature of price movements is attributed to market psychology," or the idea that people and the market will react in a similar way to similar stimuli (Janssen et al., 2015).

There are many critics of technical analysis that view it as almost black magic. Critics primarily cite the efficient market hypothesis (EMH) which states that the price is always correct and past information has already been appropriately priced into the stock. Within the EMH there are three forms: weak, semi-strong, and strong (Yaes & Bechhoefer, 1989). The weak form assumes that past information and past price movement will have no effect on the future. Semi-strong efficiency agrees with the weak form but also that the market reflects all public information and the prices quickly change with any new information. Believers in semi-strong efficiency claim an investor cannot outperform the market by trading on new, public information. Strong form efficiency claims prices fully reflect any and all available information helpful in making investing decisions. This includes both private and public data which means even insider trading information would not alter the stock price. While some authors support this, the general market equilibrium disagrees (Jordan, 1983).

For effective technical trading, John Murphy (1999) identified the "Ten Laws of Technical Trading." The first two "laws" speak to the importance of identifying long-term trends so trading can follow the same direction of the general market. Any signal can be interpreted as a buy or sell depending on the general trends of the market and the specific security. If the general trend is up, buying when the market dips can provide greater returns, but if the security is trending down, buying at a dip will just see the market continue to decline. The same holds true vice-versa, selling during price rallies works best during a downward trend (Edwards, Magee & Bassetti, 2007). Alternatively, a market may be trading rather than trending. A trading market is characterized by its general horizontal direction. Murphy recommends using the Average Directional Movement Index (ADX) to help determine whether movement is a trend or just a trading market. Finally, when a trend reverses it usually retraces a large portion of the previous trend. He refers to Fibonacci Retracements of 38% and 62% to identify how large the retracement will last which can give macro buy or sell points (Murphy, 1999).

Stochastic Oscillators

Dr. George Lane developed stochastic oscillators in the 1950s. Despite the name stochastic, Stochastic Oscillators do not derive their name from the scientific term that means random. Instead, stochastic refers to the current price relative to its price range over a period of time (Murphy, 1999). Within technical analysis, oscillators are the most common types of indicators and have a bounded range. Within this range, there are signals where a security is overbought or oversold. Stochastic Oscillators are momentum indicators, but differ from other indicators by placing a greater emphasis on recent price action. There are two components to the oscillators, *%D* and *%K*. Over the years, these oscillators have remained one of the most popular momentum signals for both long- and short-term investing. There are two types of Stochastic Oscillators, Fast and Slow. A Fast Stochastic uses a simple moving average (SMA), which makes it more sensitive to price change and can have more signals but also more false signals as volatility increases. On the other hand, a Slow Stochastic uses a smoothing element by taking the SMA of the Fast Stochastic's SMA (Kirkpatrick & Dahlquist, 2015). The formulas are:

$$\%K = \frac{(C - L)}{(H - L)}\, x\ 100$$

fast %D = 3-bar SMA of *%K*

slow %D = 3-bar SMA of *fast %D*

For *%K*, *C* represents the most recent closing price, *L* represents the low of an *N*-period range and *H* represents the high from that same range. The standard range is a 14 day period. The *%D* line is regarded as more important than *%K* because the *%K* line changes direction more often and typically before the *%D* line. If the opposite occurs and *%D* changes direction before *%K*, it often indicates a slow and steady reversal (Murphy, 1986). When using the Slow Stochastic, the original *%K* is dropped and the *fast %D* becomes the new line. Therefore, the Slow Stochastic uses the second and third formulas listed above, but changes the *fast %D* to replace *%K* (Schade, 2015).

Figure 1

Source: StockCharts.com

Figure 1 shows a graph of McDonalds' stock. Examples can be seen when to buy or sell a security using Stochastic Oscillators. Signals are given when the two components cross each other. While there are a number of points where *%K* and *%D* cross, there are stronger signals when the cross occurs outside of a determined channel defined by the bounds - typically 20 for oversold and 80 for overbought. The closer the cross occurs to the extremes, 0 and 100, it indicates a more powerful move (Schade, 2015). Stochastics also tend to work better in a trading, or horizontal market, rather than a trending market.

Bollinger Bands

Bollinger bands were first created by John Bollinger in the 1980's and served as a type of dynamic moving average to provide parameters for technical trading. One of defining features is that they adjust in size which helps accounts for price volatility around the moving average. The bands tighten during times of higher stability and grow larger with higher volatility (Kirkpatrick & Dahlquist, 2015). The bands consist of two components, a simple moving average (SMA) based on an N-period and an upper and lower limit derived as K times the standard deviation of the volatility. Historically, the value for N is 20 and 2 for K. Theoretically, 95% of data would fall within two standard deviations of the SMA but due to nonrandom and nonstationary price action, this is not necessarily true.

Bollinger Bands work best to indicate the beginning of trends when the upper and lower bounds are crossed. When a security's price reaches above the upper band, it is considered overbought and below the lower limit means the security is oversold (Leung & Chong, 2003). An overbought security should be sold or shorted and an oversold security should be purchased. When a price travels above the upper-line, the market tends to overcompensate and go too far in the other direction which can cause a rebound to quickly occur. This quick reaction allows for more trades to occur (Williams, 2013).As a result, they typically have more success in actively managed funds that can react to the overcompensation and they trade better in trending markets rather than horizontal. Additionally, Bollinger Bands may be better suited for commodities trading or exchange rate trading, where "over 90% of the… traders use technical analysis in their trading decisions" (Chen et al., 2014).

Figure 2

Source: nyselive.com

Looking at Figure 2, the stock crosses the upper band twice. First, on June 1st and again in the middle of July. These illustrate the two possible movements that can occur when a stock crosses a band. In the first example, the stock hits a high and then reverts back to the mean, closer to the middle band, which indicates an opportunity to short the security. The second example illustrates a new trend because once the stock exceeds the upper band and then continues to trend upwards. Ideally, the security would be bought at this signal but in both examples the price crosses the upper bound and sends the same signal.

As a result, new metrics can be useful to distinguish the appropriate action at each signal. In 2010, John Bollinger introduced new indicators derived from Bollinger Bands, most notably percent bandwidth (*%b*). *%b* aims to help normalize the size of the upper and lower limits over time (Williams, 2013). The formula for *%b* is:

$$\%b = \frac{(Last\ price - LowerBB)}{(UpperBB - LowerBB)}$$

UpperBB indicates the value for the upper Bollinger Band and LowerBB for the lower Bollinger Band. The other metric derived from Bollinger Bands is BandWidth. The Bandwidth helps identifies the extremes, either Squeezes where the bands are tight or Bulges where the bands are further apart. A Squeeze is identified when the BandWidth reaches a new 125-day minimum and a Bulge is a new 125-day maximum (John Bollinger webcast). In his book, Bollinger on Bollinger Bands, John Bollinger (2001) mentions using BandWidth as a volatility metric. The Bandwidth is derived entirely from standard deviations, a decreasing BandWidth indicates decreasing volatility as the standard deviation decreases while the opposite is true for increasing BandWidth.

Previous Research: Stochastic Oscillators

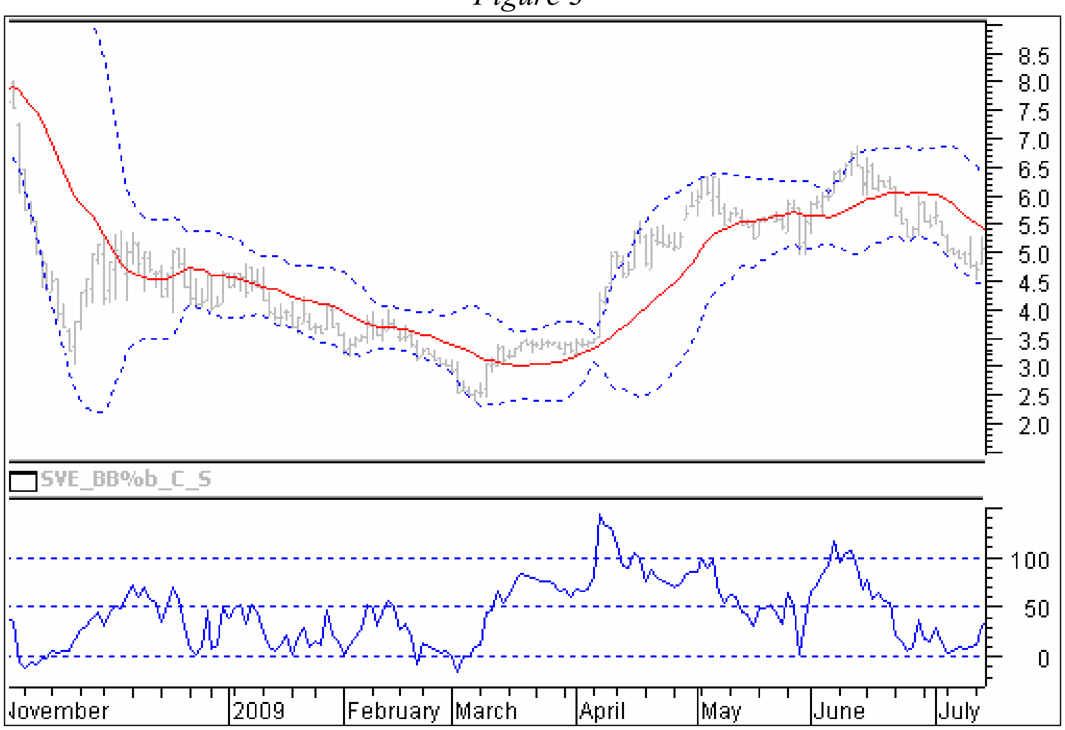
For bound oscillators such as Stochastic Oscillators, buy and sell signals occur when the oscillator surpasses the upper bound or dips below the lower bound. Research and traders have evaluated the metric's effectiveness by looking at variables for the different formulas along with the traditional upper and lower bounds of 80 and 20 respectively.

For Stochastic Oscillators, the signal occurs when the *%D* and *%K* lines cross either above or below the bounds. Jawade, Naidu, and Agrawal (2015) examined if the defined standard bounds of 20 and 80 were most effective. They looked at the Nifty futures market in India. They examine both the Relative Strength Index and Stochastic Oscillators, two momentum indicators, and their performance over a full year of data from 2012-2013. While they conclude the long signals sent below the lower bounds are accurately set to 20, they claim the upper bound should be adjusted up to 90.59 rather than 80. This means strong signals sent from crosses that occur above the traditional value of 80 have a higher tendency to send false signals. A higher value may eliminate some false signals, but there is also the risk of missing an effective signal that would have otherwise been identified (Jawade et al., 2015). The increase to the upper bound makes is less likely for the cross to occur above the bound, and therefore less likely to receive a sell signal and enter into a short trade.

Previous Research: Bollinger Bands

There are a lot of components that can impact the success of technical analysis, such as the market quality based on market capitalization and the type of market, whether that is currency exchange rates, stocks, or options. Research on historical data continues to give more insight into new metrics or refining existing metrics. For Bollinger Bands, the traditional bounds provided for the variables can be modified and different metrics can be paired with the bands, such as *%b*, to help generate better results.

Figure 3



Source: Bollinger, 2011

The chart in Figure 3 illustrates the accompanying metric that John Bollinger introduced, *%b*. This indicator can be seen below the graph of the stock price with the Bollinger Bands in place. This metric relies on upper and lower bounds similar to standard Bollinger bands but illustrates the recent price as a percent of the upper and lower bands. When *%b* goes above 100, it indicates the last price is further away from the lower bound than it has over the period of time used with %b, and if the indicator falls below 0 then the price has dropped below the lowest bound over that same period (Williams, 2013).

Hartono and Sulistiawan (2010) examined the effectiveness of overall technical analysis in 21 different countries and specifically, the impact of differing market quality. The basis of the study can help bridge the gap and allow for better comparisons between studies of technical analysis done in different countries. They hypothesized that higher quality markets lead to more profitable technical analysis, challenging the status quo that in low quality markets, the market's are less efficient so there is more to be gained from using technical analysis. However, the analysis they conduct disproved their hypothesis, illustrating a significant negative relationship between market quality and returns.

Kabansinskas and Macys (2010) looked at trading Bollinger Bands in the Baltic market to establish the optimal parameters for the variables. As mentioned before, the value for N is 20 and K is 2. However, this study looks at the ideal parameters for both short- and long-term investing. They conclude that for indicating short-term trends, N should be set to 10 and K to 1.9. Setting the variables lower for short-term trading makes the metric more sensitive and the security is more prone to exceeding or dropping below the bounds, sending more trading signals. Decreasing N decreases the days in the average so each day carries more weight in the SMA and therefore the standard deviations. For long-term investing they found the optimal parameters for N to be 50 and

K to be 2.1. This is opposite the short-term trading variables by increases the standard deviations requirements for a signal and therefore, helps eliminate false signals.

While the different variables can be used for short- or long-term investing, historical evidence points to Bollinger Bands indicating long-term investing better. Leung and Chong (2003) examine the general use of how the bands adjust to volatility by examining stock price data from 11 different countries, ranging in different market qualities, over 1985-2000. They concluded that they are better used as a long-term investment tool and simple moving averages that don't account for volatility are more effective for shorter-term investing.

While Bollinger bands adjust their width with changes in volatility, they do not adjust for volatility clustering that occurs in price distributions. Time series for financial series commonly have a fat tail or leptokurtic distribution (Chen et al., 2014). A fat tail occurs when a distribution has more values occurring outside of the standard deviations when compared to a normal distribution. In a normal distribution 99.7% of data points should fall within three standard deviations of the mean but a fat tail means more values will fall outside of this range, meaning four or five sigma events are more likely to occur. Leptokurtic is when the distribution clusters more around the mean which leads to a higher peak and a smaller standard deviation. Leptokurtic and fat tail distribution can be seen together due to the smaller standard deviation that makes higher sigma events more likely to occur (Janssen & Murphy, 2015). These distributions are more characteristic of financial series and Chen's (2014) study accounts for these by comparing adjusted and standard Bollinger bands. For the adjustment, Chen adds a GARCH (1,1) model function to the equation. This model helps describe the volatility clustering nature of financial series which in turn helps account for these distributions. Ultimately, the study concludes the GARCH (1,1) adjusted Bollinger band performs better than the standard bands because they do adjust for the nature of financial series (Chen et al., 2014).

One issue with the Bollinger Bands is that they do not cover a normal distribution. Based on a Gaussian distribution, 95.4% of prices should fall within the two standard deviations around the SMA. However, this is not the case. In 2010, David Rooke noted that based on S&P 500 prices a two standard deviation 20-day Bollinger Band only covered 88.5% of price data. This is the result because the moving average fails to correlate with historical price volatility. While the Bollinger Band does attempt to reflect changes in volatility, it only does so over a short period of time. Rooke proposed using a lag-adjusted triple exponential moving average. The resulting metric was able to capture 95.7% of price data within two standard deviation, aligning with a normal distribution (Rooke, 2010).

Methodology

This examined 20 of the largest stocks in US market and their performance from 2012-2014. Two stocks were selected from each of the market's ten sectors to represent the overall market as well as provide potential insight into how Bollinger bands and stochastic oscillators perform for the different sectors. The companies chosen are listed in Figure 4. The 2012-2014 timeline also allows for the long-term impact of the metrics to be observed. Bollinger bands have historically performed better during trending markets whereas Stochastic Oscillators perform better during trading, or horizontal markets.

Figure 4

Sector	Company	Ticker
Basic Materials	Dow Chemical	DOW
	Monsanto Company	MON
Consumer Discretionary	Amazon	AMZN
	Walt Disney	DIS
Consumer Staples	Procter & Gamble	PG
	Coca-Cola	KO
Energy	Exxon Mobil	XOM
	Chevron	CVX
Financials	Wells Fargo	WFC
	Berkshire Hathaway	BRK.B
Healthcare	Johnson & Johnson	JNJ
	Pfizer	PFE
Industrials	General Electric	GE
	3M Company	MMM
Information Technology	Apple	AAPL
	Microsoft	MSFT
Telecommunications	AT&T	T
	Verizon	VZ
Utilities	NextEra Energy	NEE
	Duke Energy	DUK

Looking at a 3-year period offers times when the market was bullish and trending up as well as trading periods. Using the S&P 500 as a benchmark for the market, the market opened at $1277.81 on January 2nd, 2012 and gained 14.7% on the year. In 2013, the market had one of its best years, growing 26.4%, and in 2014, it grew 12.4%, surpassing the $2000 mark for the first time. Compounding over the three year period, the market returned over 60%. Three other benchmarks were also selected to compare the results, the Bollinger Band's performance on its own, the Slow Stochastic Oscillator's performance on its own, and each individual stocks performance over the three years utilizing a buy and hold strategy. Those three benchmarks can be seen in Figure 5.

The stock price data was pulled from Bloomberg for each of the selected 20 companies. Any dividend information was disregarded and stock splits were noted to adjust the prices. With this data, both the Bollinger Bands and Stochastic Oscillators were calculated. For the Bollinger Bands, 20 was used for N and 2 for K. These were the values John Bollinger introduced and have been widely accepted as the standard values. For the Stochastic Oscillator, this study used the Slow Stochastic because of the longer-term trading strategy and chose to use the standard period of 14 days. The historical closing price was used as the price data for the metrics. While the intraday high and low could have been used to see if the bounds were crossed at any point, the closing price data eliminates the risk of a quick spike in the price that could cause the metric to send a false signal.

Figure 5

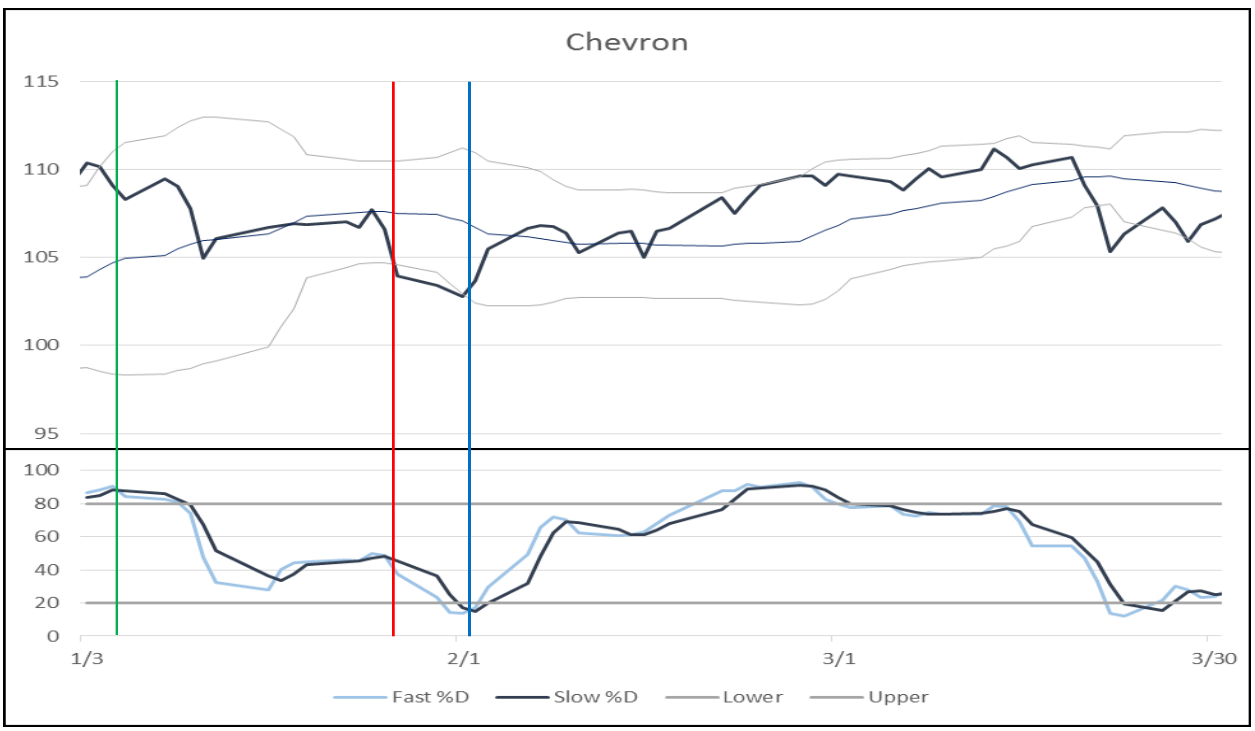
Ticker	Bollinger Bands	Slow Stochastic	Buy & Hold
DOW	56%	110%	56%
MON	22%	22%	67%
AMZN	(33%)	56%	76%
DIS	(40%)	(31%)	148%
PG	3%	12%	37%
KO	40%	75%	20%
XOM	23%	22%	8%
CVX	55%	34%	3%
WFC	0%	1%	96%
BRK.B	6%	(22%)	94%
JNJ	(3%)	50%	59%
PFE	1%	47%	42%
GE	63%	40%	39%
MMM	11%	9%	96%
AAPL	(48%)	10%	89%
MSFT	(25%)	(32%)	75%
T	20%	(14%)	10%
VZ	8%	32%	16%
NEE	(14%)	37%	74%
DUK	(2%)	(14%)	26%
Total	**7%**	**22%**	**57%**

For simplicity, the analysis equally weighted each of the companies, allocating one million dollars to each stock selected and allowed for fractions of shares to be traded to get to the even one million. The number of shares was determined based on the initial price of each stock on January 3rd, 2012. January 3rd was the first trading day of year so the amount was based on the opening price from this day. Rather than having money in each position the entire time, this study elected to close and enter into new positions over the duration of the study. However, an additional amount of money was never added or taken away from any company, allowing the returns to compound on one another. This posed a risk of different weights towards the end of the period. On the first day, each position consisted of 5% of the total $20 million portfolio. However, based on performance of the individual companies, one of the stocks could increase more than the others and become a relatively higher weight of the portfolio.

Using two metrics also posed a challenge because they do not always send the same trading signal. To counter this, positions were closed when the two metrics sent different signals and opened a position when they agreed. After a metric provided a signal, that metric gave the same signal every day until it switched positions and gave the opposite signal. Once a metric sent a short signal, the signal was treated as a short signal every day until the metric reversed and signified a long opportunity. The trading strategy entered into a new position at the open price on the day after both signals agreed with one another. For example, if the Bollinger Band had a buy signal, the position would only be taken once the Stochastic Oscillator also sent a buy signal. This dramatically reduced the total number of transactions placed, but the aim was to reduce the number of false signals. Regarding Bollinger Bands, a signal can be interpreted two different ways. First, a signal above the upper band can be interpreted as mean reverting where the security is overpriced and should be sold, or as signaling a new trend in which case the security should be bought. The study used the signals from the Bollinger Band as mean reverting. Additionally, the paper ignored the impact of dividends on returns and solely looked at capital appreciation.

Figure 6 represents an example of the trading strategy applied to three months of Chevron. The top portion of the graph illustrates the Bollinger Bands and the bottom illustrates the Slow Stochastic. At the beginning of the period, both metrics are above the upper bound. This means the Bollinger Band is giving a short signal; and once the two lines cross in the Slow Stochastic graph it also sends a short signal. At this point, illustrated by the green line, a short position was taken. The short position is held until the price dips below the Bollinger Band, identified by the red line, signifying a period of the security being oversold so a long position should be taken. Since the Slow Stochastic has not sent a long signal, the investment is pulled out of the security and sits in cash until the Slow Stochastic also indicates a buying opportunity, denoted by the blue line.

Figure 6



Hypothesis: Combining the Metrics

By combining Bollinger Bands and Slow Stochastic Oscillators the hope was to reduce the number of false signals, reduce exposure, and only invest at periods of time with superior return for the stock. Since both metrics rely on momentum, the study hypothesizes that they will normally be in agreeance with one another. However, when they do not agree and send the same signal, the hypothesis holds that those times are poor times to trade. In the times the metrics do not agree, the strategy will be out of the security, therefore decreasing the exposure to the market. When the strategy out of a position, the aim is that these are periods with an average daily return lower than the overall securities average return over the same period, effectively removing risk and exposure at these worse times. It is important to note though, worse times are not defined by periods of loss because this movement can be captured through a short position. Additionally, these worse times are independent of volatility because while higher volatility can increase returns, it also increases risk so they are not always better when risk adjusted.

Results and Analysis

After processing the three years of data, the combined strategy resulted in a negative 1.53% loss. Looking at each individual stock's performance using the combined metrics, six stocks outperformed the Bollinger Band, two outperformed the Slow Stochastic, and only three stocks outperformed a simple buy and hold approach: Coca-Cola (KO), ExxonMobil (XOM), and Chevron (CVX). Ultimately, only 9 of the 20 securities actually had a positive return whereas all 20 securities went up over the three years.

Figure 7

Ticker	Combined Return	Bollinger Bands	Stochastic Slow	Buy & Hold
DOW	51%	56%	110%	56%
MON	7%	22%	22%	67%
AMZN	(20%)	(33%)	56%	76%
DIS	(45%)	(40%)	(31%)	148%
PG	(7%)	3%	12%	37%
KO	30%	40%	75%	20%
XOM	10%	23%	22%	8%
CVX	20%	55%	34%	3%
WFC	5%	0%	1%	96%
BRK.B	(12%)	6%	(22%)	94%
JNJ	6%	(3%)	50%	59%
PFE	2%	1%	47%	42%
GE	24%	63%	40%	39%
MMM	(3%)	11%	9%	96%
AAPL	(12%)	(48%)	10%	89%
MSFT	(36%)	(25%)	(32%)	75%
T	(14%)	20%	(14%)	10%
VZ	10%	8%	32%	16%
NEE	(22%)	(14%)	37%	74%
DUK	(25%)	(2%)	(14%)	26%
Total	**(1.5%)**	**7.2%**	**22.1%**	**56.6%**

The best performing stock over the three years was Disney, returning 148%, or more than 35% annualized. Interestingly, this was the worst performing stock from the combined metrics, losing 45% over the three years. Even using only Bollinger Bands, the better performing metric on its own, experienced an excess of a 30% loss. Looking deeper into the price chart, there was not a good time to enter a short position on Disney. Entering into a short position only exposed the position to the increasing stock price. Over the trading period, the combined metrics signaled for 13 trades, six of them long positions and seven short positions. The average long position lasted for 25 trading days and saw a positive return of 2.8% for each trade. However, since the stock price was only appreciating, there was not good time to enter into a short position and each of the seven short positions averaged over a 10% loss. For the two metrics to both agree on a short position, the price had to go above both of the upper bounds for the metrics. Then, to get out of the position, the momentum of the stock price had to shift enough for one of the lower bounds to be crossed and a buy signal to be sent. Since the stock price continued to increase and increase, there were very few times the momentum switched and dipped below the lower bound, leaving the position exposed in each short position for an average of 75 trading days, three times the average long position.

On the opposite end of the spectrum, the energy sector did not perform well over the three years and ExxonMobil returned 8% while Chevron only returned 3%. Both of these stocks were in trading environments over the three years, fluctuating up and down but remaining generally horizontal. This trading market provided better short opportunities since the price made downward movements over the period. The strategy opted to treat the signals from Stochastics and Bollinger Bands as mean-reverting, which is designed for a trading environment where the movement can be captured both ways. As expected, the trading strategy, when applied to Chevron and ExxonMobil, exceeded the return of a buy and hold for both stocks. However, when the two metrics were combined they still did not outperform either metric on its own.

This prompted me to examine the performance of long positions compared to short positions. Over the course of trading the 20 securities over the three years, roughly the same number of each position were taken. The trading strategy entered into 173 short trades and 179 long trades. However, taking the sum of all returns from the shorts, they lost 296%, which comes out to an average loss of 1.71% per short. For the longs, they saw a positive return of 270%, or an average gain of 1.51% each time a long position was entered. This is largely a result of the general market, since the market continually went up, there were very few opportunities to capture a positive return on shorts. When a short position was taken in a security, the stock were not likely to go down, and rather went up and resulted in negative returns.

Combining the Slow Stochastic and Bollinger Bands only outperformed either of the metrics on their own in 8 of the 40 possible outcomes. This directly contradicts the hypothesis that the combination would reduce false signals and signal trade at superior times than an individual metric. Instead, waiting for both metrics to agree ended up resulting in redundancy, one metric would send a signal but the trade wouldn't be executed until the second metric also agreed. An example of this can be seen with Proctor & Gamble in October 2012. Looking at Figure 8, the two metrics were both in a short position until the Bollinger Band sent a long signal on the 10th. Rather than executing the trade, the strategy waited for both metrics to agree and didn't execute the trade until three trading days later, on the 15th, after the stock had gone up \$0.57, or almost 1%.

Figure 8

Date	Close Price	Bollinger Band Position	Slow Stochastic Position
10/16	69	Buy	Buy
10/15	**68.71**	**Buy**	**Buy**
10/12	67.94	Buy	Sell
10/11	68	Buy	Sell
10/10	**68.14**	**Buy**	Sell
10/9	68.7	Sell	Sell
10/8	69.1	Sell	Sell

The third part of the hypothesis reasoned that since the two metrics would not always agree with each other, there would be periods where the capital invested would be taken out of the security and held in cash. The study hypothesized that these periods would reduce the market exposure and the strategy would only trade during times of higher than average daily return. To measure this, the average daily return was calculated on each position taken. To account for the compounding effect, the average was calculated using higher order square roots and taking the total compounded return of the longs and shorts to the radical of the number of trading days, which is shown below.

$$Daily\ Return = \sqrt[Trading\ Days]{Return}$$

I chose to separate out the long trades and short trades since the average long and short provided such different returns. As mentioned above, the average long position returned 1.5% whereas the average short suffered a loss of 1.7%. Figure 9 shows the results of each stock's return after adjusting for the limited exposure the trading strategy has. The average long position had a higher exposure adjusted return than a buy and hold strategy for 12 of the 20 securities, while Chevron was the only stock where the short positions also exceeded the average return of the buy and hold. This is in line with Chevron's results. Out of the 20% Chevron returned using the combined trading strategy, short positions accounted for 16% of the compounded return. Still, the average long position was still 0.003% lower than the daily return of the buy and hold strategy, contradicting the hypothesis of trading at times with superior returns.

Figure 9

Compounded Return			
Ticker	Short	Long	Buy & Hold
DOW	0.014%	**0.157%**	0.057%
MON	(0.044%)	**0.101%**	0.065%
AMZN	(0.075%)	0.001%	0.073%
DIS	(0.149%)	0.107%	0.116%
PG	(0.060%)	0.021%	0.041%
KO	0.022%	**0.070%**	0.024%
XOM	(0.042%)	**0.047%**	0.009%
CVX	**0.056%**	**0.010%**	0.004%
WFC	(0.069%)	**0.140%**	0.086%
BRK.B	(0.054%)	**0.101%**	0.085%
JNJ	(0.055%)	**0.116%**	0.060%
PFE	(0.050%)	**0.071%**	0.045%
GE	0.029%	**0.048%**	0.042%
MMM	(0.027%)	0.071%	0.086%
AAPL	(0.020%)	(0.024%)	0.081%
MSFT	(0.132%)	0.041%	0.072%
T	(0.047%)	(0.001%)	0.013%
VZ	(0.005%)	**0.029%**	0.019%
NEE	(0.088%)	**0.075%**	0.071%
DUK	(0.089%)	0.001%	0.030%
Weighted Average	**(0.051%)**	**0.051%**	**0.054%**

Additional Scenarios

Fast Stochastic

The original trading strategy coupled the Slow Stochastic and the Bollinger Bands. The Slow Stochastic uses an additional three day SMA of the Fast Stochastic to smooth out the movement of the two lines. As a result, the Slow Stochastic does not respond as quickly to changes in a stock price's momentum. After the initial results, the Bollinger Bands were combined with the Fast Stochastic to examine how the different Stochastics performed in periods of upward trends and while combined with the Bollinger Bands. The results in Figure 10 show that the more sensitive Fast Stochastic faired worse on its own than the Slow Stochastic. Additionally, the combined position returned negative 8.1% compared to the Bollinger Band combined with the Slow Stochastic which only had a 1.5% loss.

Figure 10

Ticker	Combined Position	Fast Stochastic	Slow Stochastic	Buy & Hold
DOW	82%	172%	110%	56%
MON	(2%)	29%	22%	67%
AMZN	(30%)	61%	56%	76%
DIS	(50%)	(39%)	(31%)	148%
PG	(11%)	(5%)	12%	37%
KO	10%	17%	75%	20%
XOM	5%	13%	22%	8%
CVX	6%	3%	34%	3%
WFC	(30%)	(31%)	1%	96%
BRK.B	(22%)	(26%)	(22%)	94%
JNJ	2%	24%	50%	59%
PFE	(11%)	(2%)	47%	42%
GE	18%	34%	40%	39%
MMM	5%	60%	9%	96%
AAPL	(60%)	(18%)	10%	89%
MSFT	(39%)	(29%)	(32%)	75%
T	(0%)	12%	(14%)	10%
VZ	(0%)	27%	32%	16%
NEE	(22%)	14%	37%	74%
DUK	(12%)	28%	(14%)	26%
Average	**(8.1%)**	**17.2%**	**22.1%**	**56.6%**

Much in line with the expectations of a more sensitive metric, using the Fast Stochastic led to 51 additional short positions and 18 additional long positions. However, the 224 short trades averaged a loss of 2.25%, much worse than the 1.7% loss achieved from combining the Slow Stochastic. On the flip side though, the long positions also fared better, with an average return of 1.7%, compared to the 1.5% from the Slow Stochastic. The more sensitive metric also increased the market exposure by investing the capital in the security more than 10% more often. While the overall exposure increased, there was an average of 20 fewer trading days invested in a long position. This means that there were more long trades, with a higher average return, and with fewer days exposed. After adjusting the average long position to account for exposure, the average daily return came out to 0.071% compared to 0.051% from the Slow Stochastic and Bollinger Bands combined. Even more significant, this number exceeds the 0.054% daily average return of securities using a buy and hold strategy. The trading strategy signified a long opportunity for 223 trading days in the three year, so that is to say, the average daily return of these 223 days exceeded that of the average market return. While it only represents half of the trading strategy, the combined metrics signaled long trades at better times and limited exposure to periods where the securities did not perform as well, agreeing with the part of the hypothesis regarding exposure.

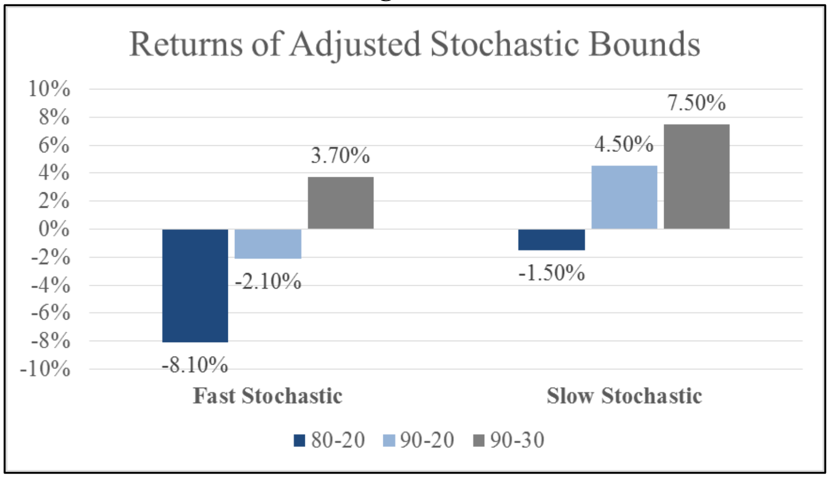
Modified Stochastic Bounds

After identifying that the average short lost money and the average long gained money, the Bollinger Bands were adjusted to try and achieve better results. The traditional bounds are set at an upper bound of 80 and a lower bound of 20. The bounds are significant because unless the two lines of the Stochastic cross outside of the bounds, no signal is sent. When the cross occurs above the upper bound, it sends a signal that the security is overbought and should be sold or shorted. Below the lower bound, the security is oversold and a cross denotes a good buying opportunity.

As Jawade, Naidu, and Agrawal note, the lower bound is accurately set to 20. However, the more optimal upper bound within the Nifty Futures Market was actually 90.59. Increasing the upper bound decreases the likelihood of a cross occurring above it, which decreases the chance of a signal to take up a short position. Since the average short performed so poorly, decreasing the probability of sell signals could eliminate costly short positions. To test this, the upper bound was adjusted to 90 and ran a scenario combining the Slow Stochastic and Bollinger Bands and a scenario with the Fast Stochastic and Bollinger Bands. Both of the new scenarios performed better, as expected. The increase to the upper bound resulted in a 6% increase. The combined Slow Stochastic and Bollinger Band return 4.5% and the Fast Stochastic and Bollinger Band only lost 2.1%.

To further try to capture the upward trend of the market, a third scenario was run with different bounds; this time increasing the lower bound from 20 to 30. Theoretically, a higher lower bound would allow for *%K* and *%D* to fall below the bound more often and therefore signal more oversold periods. Ideally this would provide two benefits, the first being the increased number of long positions, the second benefit would be exiting out of short positions quicker since the signal will flip to long more often. Once again, as expected the scenarios both performed better with a 3% increase to the Slow Stochastic and Bollinger Bands strategy and the combined Fast Stochastic and Bollinger Bands returning 6% better. Rather than 173 short positions and 179 long trades when using the 80-20 bounds, the adjusted 90-30 bounds only took 97 short positions with an average loss of 1.4% and 214 long positions averaging a 1.33% return. Figure 11 combines the three scenarios to show the increasing return with each increase to the bounds.

Figure 11

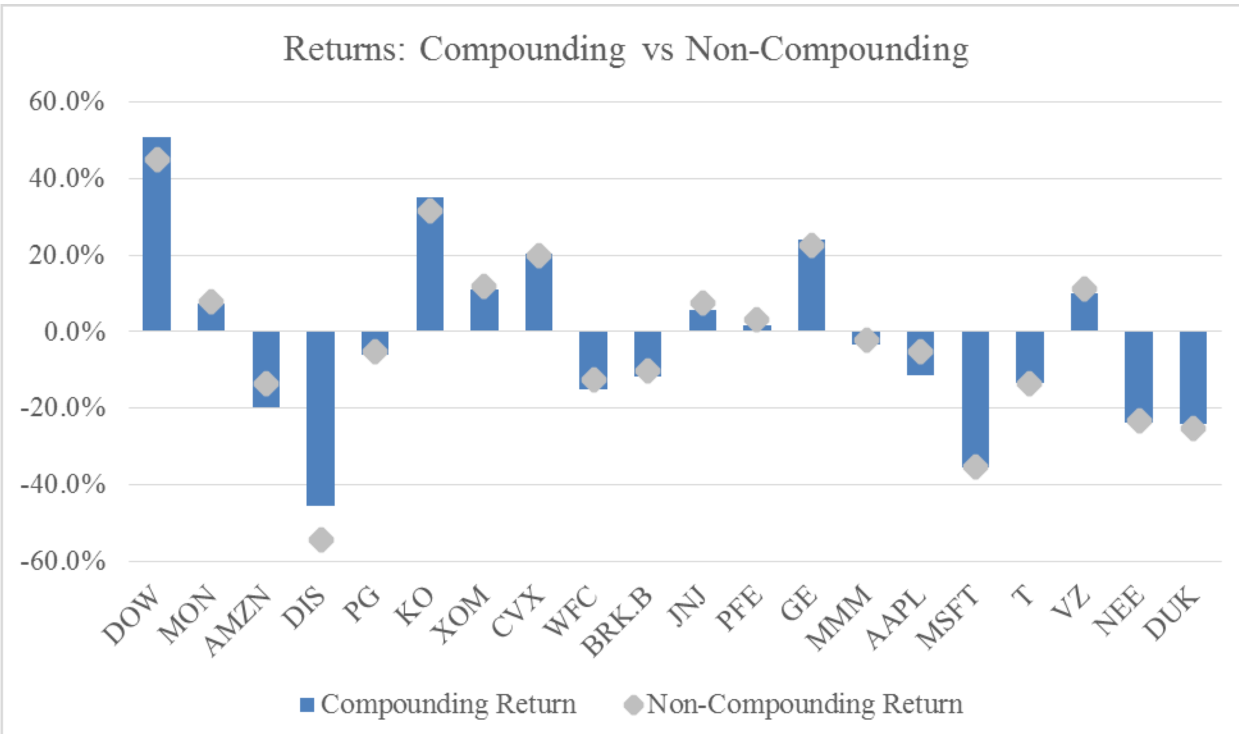


Impact of Compounding

When taking a position in an equity, each trading day sees the returns compound on the previous day since the percent change is applied to the most recent amount rather than the initial amount. Similarly, the initial scenario allowed for each subsequent trade to compound on the previous trade and continue the process of daily compounding within each security. The next scenario ran removed this component from the strategy. Each trade would receive the same capital investment regardless of the previous performance of the stock. To illustrate compounding, the table below shows three trades using an initial investment of $100. When the results compound, each subsequent return is applied to the previous balance; whereas without compounding, the returns are only applied to the initial investment. With three positive returns, the compounding provides a higher ending number, but if the scenario were flipped and there were three negative returns, the compounding result would be lower number than non-compounding.

		Compounding		Non-Compounding	
	Return	Calculation	Result	Calculation	Result
First Trade	10%	100 + (100 * 10%)	$ 110.00	100 + (100 x 10%)	$ 110.00
Second Trade	6%	110 + (110 * 6%)	$ 116.60	110 + (100 x 6%)	$ 116.00
Third Trade	15%	116.6 + (116.6 * 6%)	$ 134.09	116 + (100 x 15%)	$ 131.00

By removing the compounding, the results were anticipated to be closer to zero. For the securities with positive returns, the benefits of compounding positive returns on one another would be diminished. The results would still remain positive, but less positive. The same was expected from stocks with negative returns, they would still have negative returns, but less negative and closer to zero. The results were somewhat in line with expectations; overall the total return improved by 23 basis points to a loss of 1.3%.



Further Research Questions

The results of the original scenario did not yield support for any part of the hypothesis. Despite this, there are still further areas of analysis and questions to further examine the benefits of combining the two metrics, the merits of technical analysis, and applying a strategy to the actual markets.

Combining the Fast Stochastic and Bollinger Band provided the most support for the hypothesis about timing the market and only exposing the investment when the return is above average. The average day in a long position returned 0.071% compared to the average daily return of 0.054% for a buy and hold strategy. However, this only represents the long positions, roughly half of the population of trades. Looking at the short positions, the average trade lost 1.5%. But there were still many profitable short positions taken. Out of the 173 short positions, 87 had a negative return which leaves 86 short positions that were profitable. Further research could be done to understand what caused certain short positions to still have a positive return. Examining all of the short trades could help identify other factors or patterns in the price data that cause the trade to either generate a profit or a loss. Additionally, there were 43 short trades that fell below a 10% loss at some point during the trade but only 22 of those trades ended below 10%. This demonstrates poor timing for the investments - a short position was taken and while the price went up in excess of 10% after the trade, the price eventually dropped down to a loss less than 10%. The price peaked at a point and make a move down, but the timing of entering the short initially was too soon, coming before the price peaked and began its fall.

From 2012 to 2014 the market continuously appreciated, making it difficult to use momentum metrics that signal for short positions. Replicating this study over a period of time when the market is in a trading environment would allow for a better examination of the trading strategy's short signals. The S&P 500 had a 0.7% loss in 2015 and only a 2.3% return during the first quarter of 2016. These periods have large swings both up and down that would allow for the trading strategy to play out in multiple different scenarios to see how it performs during times of increasing, decreasing, and horizontal price movement.

John Bollinger has derived two new metrics from his Bollinger Bands. The first being *%b* and the second is BandWidth. A variation of Bandwidth, the %BandWidth applies a raw stochastic to the BandWidth over the previous 125 days. Rather than setting the bounds at 80 and 20, %BandWidth's bounds move over time. The upper bound, or 1.0 indicates a Bulge, the highest BandWidth over the past 125-days, while the lower bound, 0.0 indicates a Squeeze, the lowest BandWidth from the period. When the %BandWidth stays near either extreme for a period of time, 0.0 or 1.0, the reversal away from the Bulge or Squeeze indicates the end of a trend and a momentum shift (Bollinger, 2011). Removing the Slow Stochastic Oscillator and applying the %BandWidth raw stochastic could add a dynamic element to the strategy by indicating price trends before they occur.

Conclusion

Ultimately, the results did not strongly support the hypotheses, but despite this, there were portions of the analysis that indicated strong support for technical analysis and the combination of Stochastic Oscillators and Bollinger Bands. One of the largest hindrances to the results were the general macroeconomic conditions. The economy was recovering from a recession and the economy was performing strongly during all three years. Regardless of the trading strategy, regardless of fundamental or technical analysis, the macroeconomic conditions play a factor in trading and identifying the trends will provide crucial information about the stock market. The economic conditions are not only observed through fundamental analysis. Technical metrics such at %BandWidth can give insights into trends. These trends also do not only apply to the broad market; each sector and each individual stock experiences unique environments and factors that will impact them. While the average stock selected returned 57%, the energy sector did not perform as well over the three years, only averaging a 5% return. That sector had downward pressure during that period whereas Disney was experiencing an upward trend in excess of the market by almost 100%.

Combining the two metrics presented a set of challenges in addition to the possible benefits. Both of the metrics rely on momentum for their signals and as such, they generally provided the same signals at a similar time. However, since the strategy required both of the metrics to agree with one another, it created redundancy. While one metric may have provided a signal at a good time to enter a position, it often took additional days for the metrics to agree, missing out on the initial days of the trade which may have yielded more return. On the other hand, combining the two metrics allowed for reduced exposure to the market since the metrics sent different signals a quarter of the time. Less exposure reduced the general risk associated with investing in the market. Adjusting the results for the reduced risk and exposure showed the return for some trades, particularly long trades, took place at better times than the average. The best results came from combining the Fast Stochastic and Bollinger Bands where the average daily return of a long position was 0.071%, or 19% annualized, beating the daily market return.

Both of the metrics sent signals to enter into a position. However, timing the entrance into a position is only half of the challenge. Getting in at the best time does not guarantee superior return. Exiting a position also requires timing. There are two different types of timing an exit from a position. The first is knowing when to get out of a losing position. There were three separate trades with a loss exceeding 20%. Manually exiting a position before receiving a signal could prevent the further loss of money compared to riding out the trade until the signal flips. There is no hard and fast rule to apply for exiting losers. The other timing pertains to getting out of a position before it begins slipping and decreasing the return (DraKoln, 2008). Using a momentum indicator such as the Bollinger Bands can help with this and provide signals when the momentum is flipping. However, the price does not always cross a threshold for the signal to be sent so the combined strategy remained stuck in the position until a large enough shift in momentum occurs to cross the threshold.

Trading stocks always changes and evolves, investors will try new strategies to beat the market, but once a strategy proves itself in the market and continually returns alpha, more people adopt it until the advantage is lost. The Efficient Market Hypothesis claims all public knowledge is absorbed and reflected in the stock prices, including trading strategies and information. However, only a small portion of investors use technical analysis so even with the Efficient Market Hypothesis, the advantage still exists which can be seen in parts of this research and analysis that illustrates the ability to beat the market. Even if only through the long signals with the Fast Stochastic Oscillators, there remains the capability of using Bollinger Bands and Stochastic Oscillators to achieve superior return.

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