Georgia Institute of Technology
Machine Learning For Trading
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Project 6: Manual Strategy

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Manual Strategy - CS 7646

Introduction

According to the Efficient Market Hypothesis, historical price data and expectations are already factored into the cost of any given stock and as such it is impossible to exceed market average returns using technical analysis. However, in this assignment I attempt to create a robust manual trading strategy that can optimize my returns between a given period, specifically for the security of JP Morgan Chase and Co. To do this, I will identify several technical indicators, propose a strategy that combines the use of said indicators, and compare my in-sample results to an out-of-sample test set as well as a theoretically optimal trading strategy on the same in-sample set. Note: the symbol used in the graph below and all of the graphs in this paper is JPM (denoting the security of JP Morgan and Chase Co.)

Part I: Indicators

1.1 Simple Moving Average (SMA)

The simple moving average, also known as the rolling mean, is the average of all of recent closing prices within a fixed number of periods (ie. last n days).

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

where:

A_n = the price of an asset at period n

n = the number of total periods

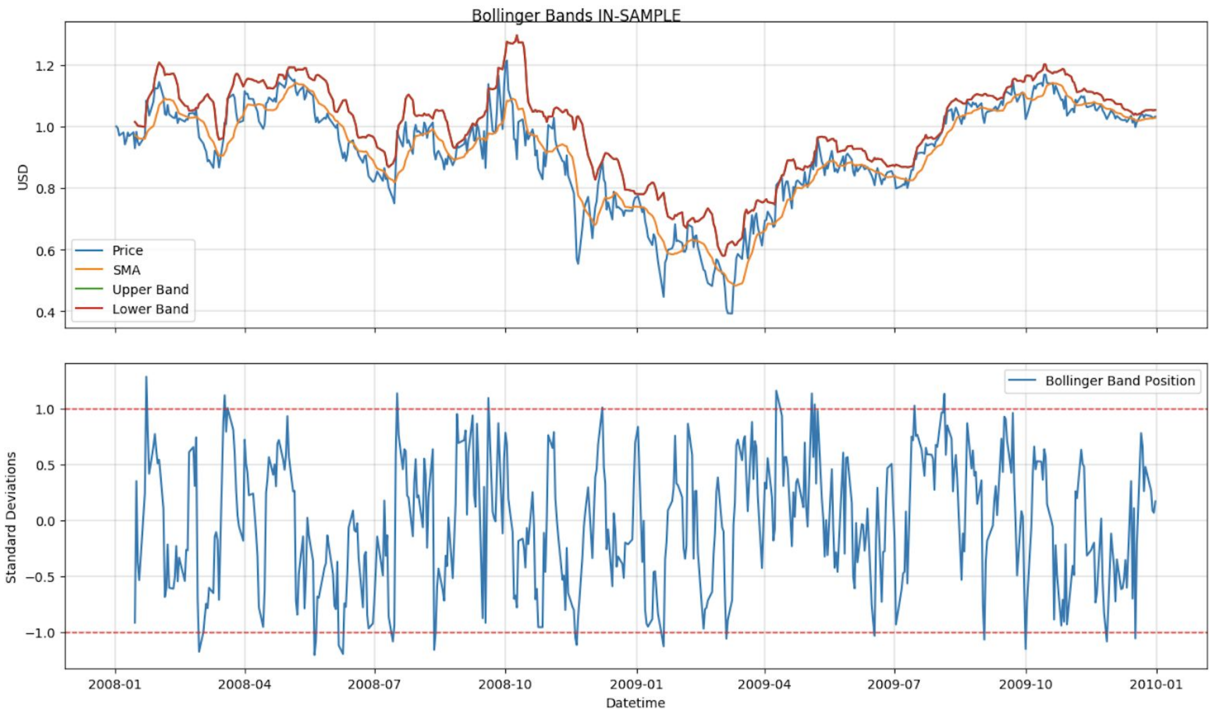
This type of technical indicator is interesting because it can be adjusted for different ranges of time periods. For example, a small value of n is more sensitive to sudden spikes/drops in a stock's price and would show more short-term changes in a stock's price trend, where as a large value of n isn't as susceptible to outliers in the price data and would show more long-term changes in a stock's price trend. As such, this indicator is very flexible and can be used for a variety of different strategies. Typically, the SMA itself is used to determine if the price of a stock will continue its trend up (positive slope of SMA line) / down negative slope of SMA line) or reverse. However, in my case I chose to use the SMA to form a different indicator called the Price-to-SMA ratio. This indicator is simply calculated by taking the price of a security at a given point and dividing it by its corresponding SMA at that point (Price-to-SMA ratio = Price ÷ SMA). This indicator is specifically useful because it tells us how far above (>1) the current price is to the SMA or how far below (<1) current price is in relation to the SMA. As such, this indicator was used in my experiment to pinpoint moments of price abnormality in hopes of maximizing my return in relation to period window. (**Note:** the settings used for this indicator for the manual strategy were window_size = 10 days, upper_threshold = 1.2, lower_threshold = 0.8)

1.2 Bollinger Bands

The second indicator I used for my technical analysis was the Bollinger Bands indicator. This indicator makes use of the simple moving average to find an upper bound and lower bound according to a set number of standard deviations from the mean (SMA). These upper and lower bounds are called the upper and lower band respectively, and the SMA is also often called the “middle band”. The calculations required around the Bollinger Bands are as follows:

* Middle Band = 20-day simple moving average of the price (SMA)
* Upper Band = 20-day SMA + (20-day standard deviation of price x 2)
* Lower Band = 20-day SMA - (20-day standard deviation of price x 2)
* Bollinger Band Position = (Price - 20-day SMA) ÷ (20-day standard deviation of price x 2)

Accordingly, the specific portion of the Bollinger Bands that I chose to look at for my strategy was the Bollinger Band Position. This indicator is a measure of volatility in stock price and is typically expressed in terms of its position within the range of [1, -1] units of standard deviation. If the Bollinger Band Position is at 1.0, then the current stock price is 2 standard deviations above the 20-day SMA, and if the Bollinger Band Position is at -1.0, then the current stock price is at 2 standard deviations below the 20-day SMA.
The window size and the number of standard deviations to consider as units were taken from research as general “rules of thumb”, and as such were used in my calculations. As you can see in the figure below, there are points in the Bollinger Band Position graph that show standard deviation units above 1.0 (2 standard deviations) and below -1.0 (2 standard deviations). These are considered moments of high volatility in the stock price. As a result, this kind of indicator is very useful when trying to predict reversals in stock price that could lead to large profit margins (buying very low or selling very high with respect to the prices that may follow “eventually”). In my strategy, after tuning the parameters, I found that a range of [-0.9, 0.9] were ideal units of standard deviation (0.9 *2 standard deviations = 1.8 standard deviations from the SMA) for my strategy.

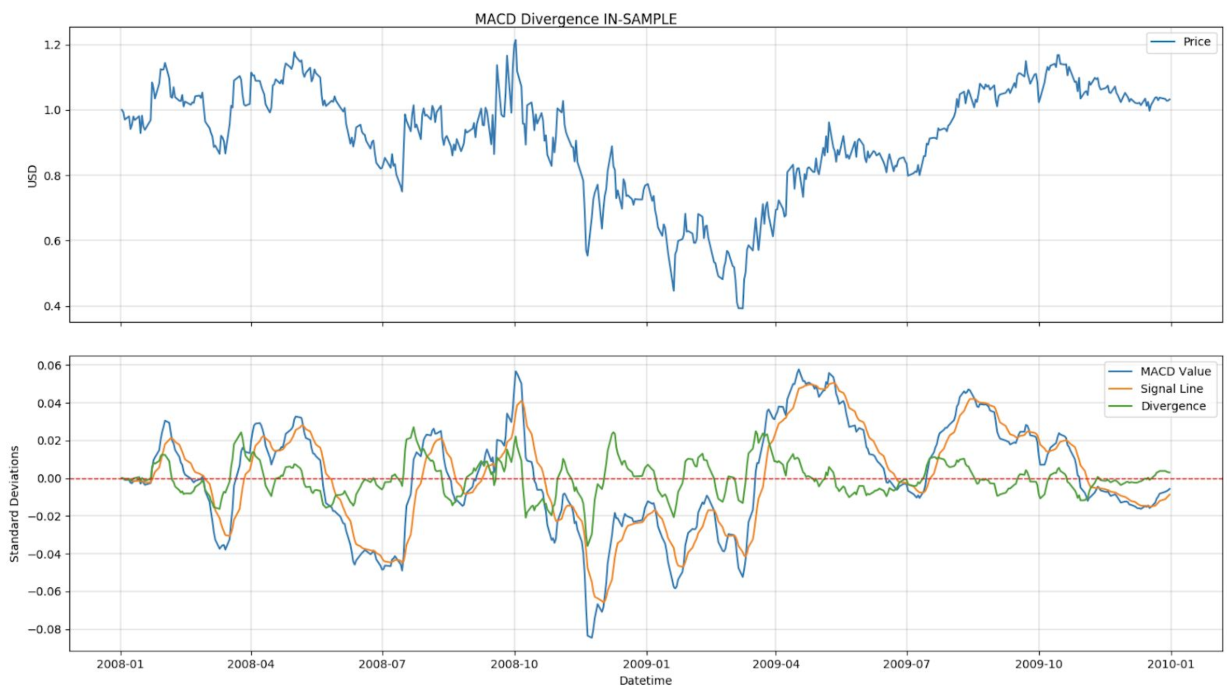


1.3 Moving Average Convergence Divergence (MACD)

The MACD is a trend-following momentum indicator that expresses the relationship between two exponential moving averages across short and long term periods. The following calculations are necessary when using the MACD indicator:

* EMA 12 = 12-day exponential moving average of the price (EMA)
* EMA 26 = 26-day exponential moving average of the price (EMA)
* MACD Value = EMA 12 - EMA 26
* Signal Line = 9-day exponential moving average of the MACD
* Divergence = MACD Value - Signal

The MACD measures momentum by subtracting the exponential moving average of the past 26 days from the exponential moving average of the past 12 days. A positive MACD value indicates a positive momentum in that the most recent window (past 12 days) has a higher value than that of the past 26 and as such is on the "rise". The opposite is true as well for measuring its momentum downward. As you can see in the graphs below, the moments where the MACD Line and the Signal Line intersect are the exact points when the Divergence line is at y=0. Accordingly, these moments are close after large dips or spikes in the stock price. As such, the MACD is typically not considered a leading indicator (in that it can predict large price reversals before they happen), but more of a lagging indicator (confirming these reversals). However, while the MACD indicator may be a lagging indicator, the hope is that if we can confirm a reversal very shortly after it has happened, we can still jump on the bandwagon and ride the benefits of the reversal as much as possible. Thus, I chose to use this Divergence indicator (moment of crossover is when Divergence = 0) in my strategy to help confirm reversals points in conjunction with my other indicators.

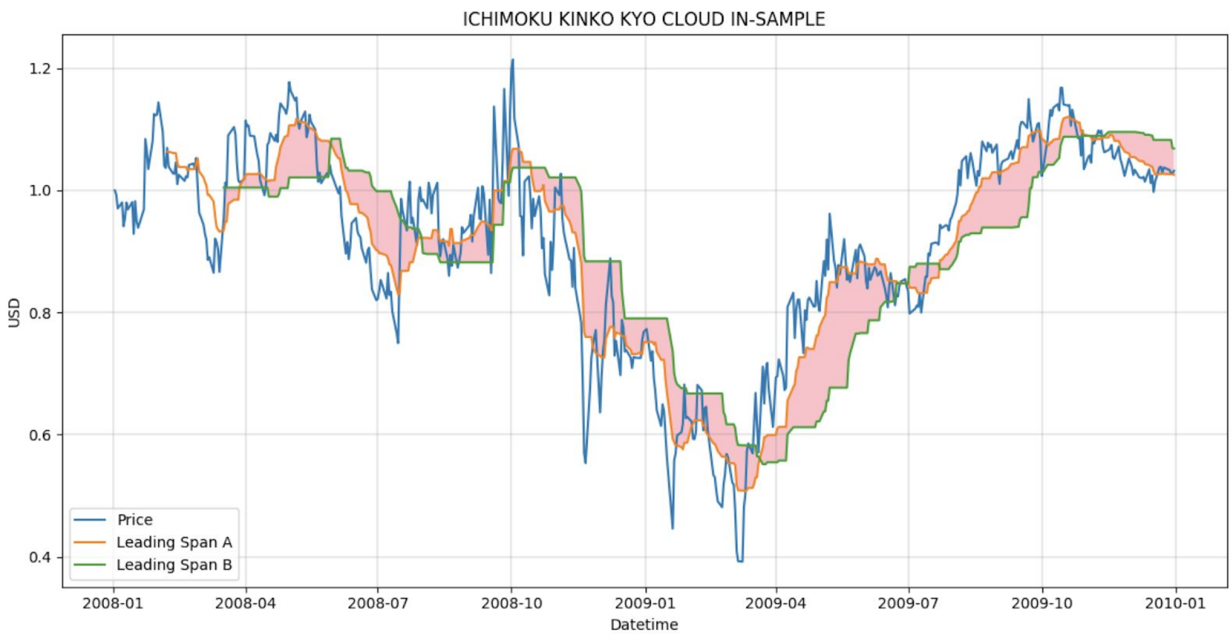


1.4 Ichimoku Kinko Kyo

The last indicator I chose to use for my trading strategy was the Ichimoku Kinko Hyo indicator. This indicator was invented by a Japanese newspaper writer, and was developed with the purpose of being an all-in-one indicator. For the purposes of my trading strategy, I chose to only use one part of this indicator, as I will later explain. The Ichimoku Kinko Hyo consists of five sub-metrics that are calculated as follows:

* Tenkan-sen (conversion line) = (highest price + lowest price over the past nine periods) ÷ 2
* Kijun-sen (base line) = (highest price + lowest price over the past 26 periods) ÷ 2
* Senkou Span A (leading span a) = (conversion line + base line) ÷ 2
* Senkou Span B (leading span b)= (highest price + lowest price over the past 52 periods) ÷ 2

In particular, I chose to use the Ichimoku cloud, which is the area encapsulated by the Leading Span A and the Leading Span B. This "cloud" attempts to forecast key areas of support and resistance that the stock prices may find in the future. Accordingly, prices that fall outside of the cloud are thought to be indicators of the current trend (below the cloud = down trend, above cloud = upward trend, within the cloud = trendless). As a result, I used the Ichimoku Cloud as my indicator to determine the trend of a price with hopes of it being a good leading indicator.

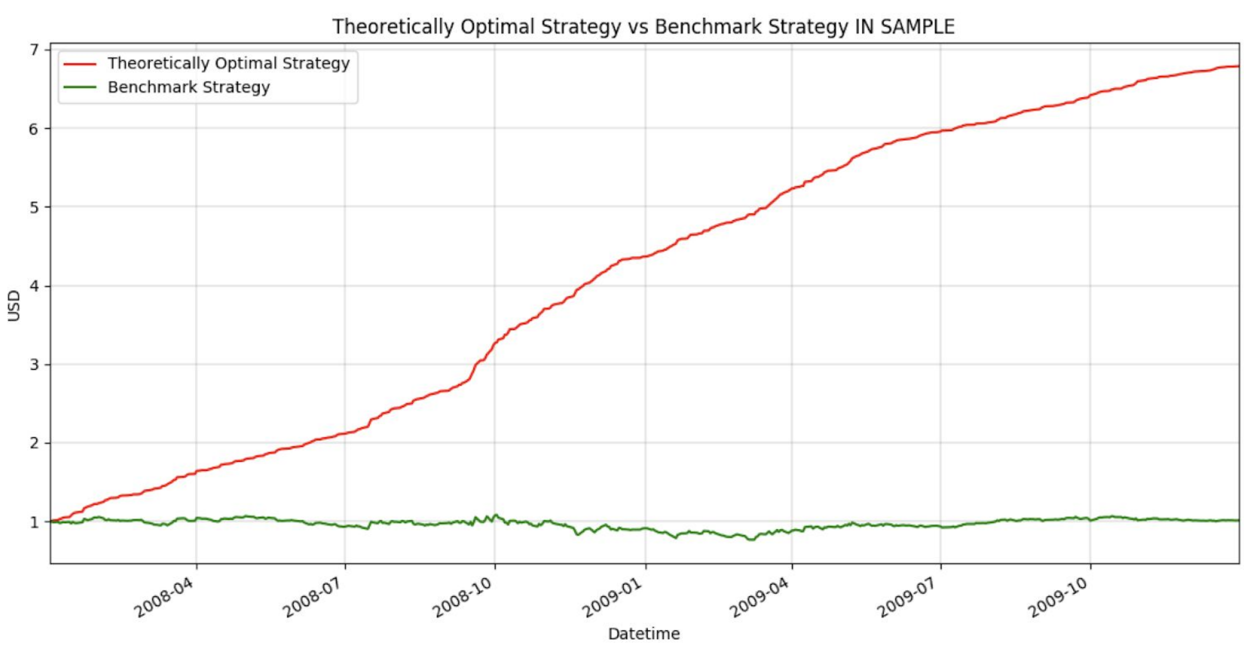


Part II: Theoretically Optimal Strategy

The theoretical optimal strategy is allowed to look into the future, and as such, on any given day it should make the most optimal decision to buy or sell a stock (according to buy-low, sell-high goal) because it would know whether the price of the stock will rise or fall in the near future. In addition, this strategy is optimal because it can make use of making Buy and Sell orders in a single day. As such, the strategy used here was as follows:

For each day in trading_range:
  If price_today < price_tomorrow:
    Enter a Long position (Buy 1000 shares of JP Morgan Chase and Co.)
  Else If price_today >= price_tomorrow:
    Enter a Short position (Sell 1000 shares of JP Morgan Chase and Co.)
  If position_yesterday == Long:
    Exit Long Position (Sell 1000 shares of JP Morgan Chase and Co.)
  Else If position_yesterday == Short:
    Exit Short Position (Buy 1000 shares of JP Morgan Chase and Co.)

In addition, this strategy along with my manual strategy were tested against a benchmark strategy to measure relative performance. This benchmark strategy is outlined as follows: on the first valid trading day within the range Buy 1000 shares of JP Morgan Chase and Co. and hold onto it for the duration of the trading range (doing nothing else in between). The results of the Theoretically Optimal Strategy vs Benchmark Strategy can be seen in the graph below. Note: the y-axis represents the value of the portfolio in units of 100,000 USD. As you can see, the Theoretically Optimal Strategy ends at a portfolio value that is almost 7x that of the benchmark strategy.



	Benchmark In-Sample	Theoretically Optimal In-Sample
Cumulative Return	$1,232.49	$578,610.00
Average Daily Return	$16.88	$381.68
Std Dev of Daily Return	$1,704.12	$454.78

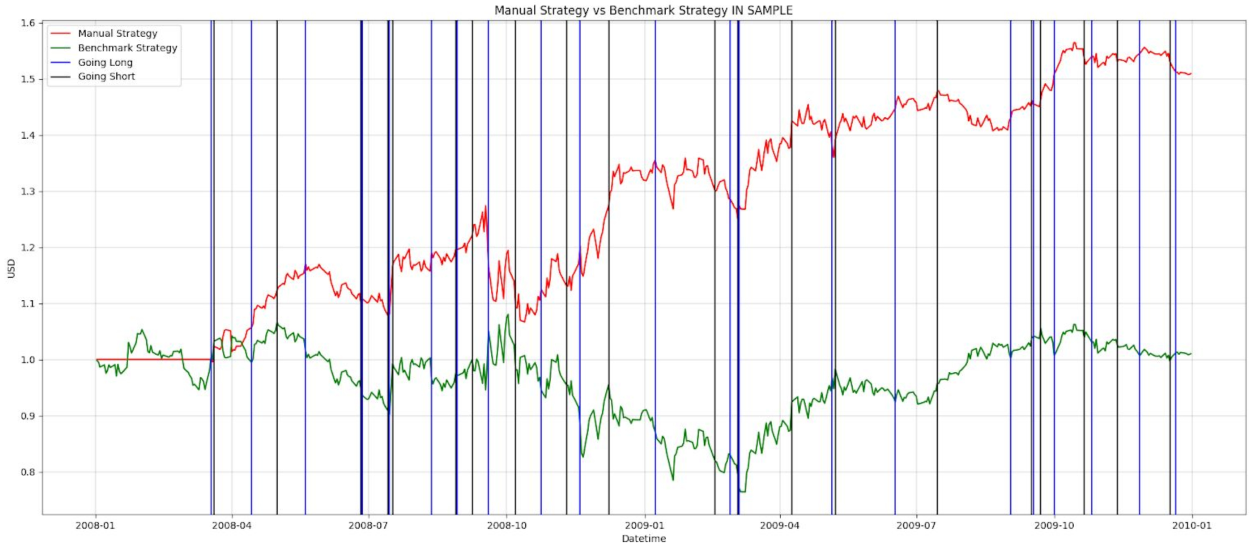
Accordingly, as noted in the table above, the Theoretically Optimal Strategy beats the Benchmark strategy in all areas (Higher Cumulative Return, Higher Average Daily Return, Lower Standard Deviation of Daily Return). As such, not only is this strategy lucrative in the fact that we profited $578,6100, but it is also consistent given by the lower standard deviation of daily return and the steady increase in portfolio value seen in the graph above.

Part III: Manual Rule-Based Trader

To compare against the Theoretically Optimal Strategy that “cheats” by analyzing future prices in conjunction with historical prices, I sought to craft a manual rule-based strategy that could compete with this optimal strategy without being able to see future prices (using only technical analysis). As a recap, the technical indicators I incorporated into my strategy were Price-to-SMA Ratio, Bollinger Band Position, MACD Divergence, and Ichimoku Cloud. The general strategy was to use the Ichimoku Cloud to determine a good entry point to start trading, then use the Price-to-SMA Ratio and Bollinger Band Position to measure volatility of the stock price, and then finally confirm with the MACD divergence to see if this point is post-reversal. Accordingly, restrictions were set in place so that the trader couldn’t keep selling or buying consecutive days in a row. As such, the strategy was as follows:

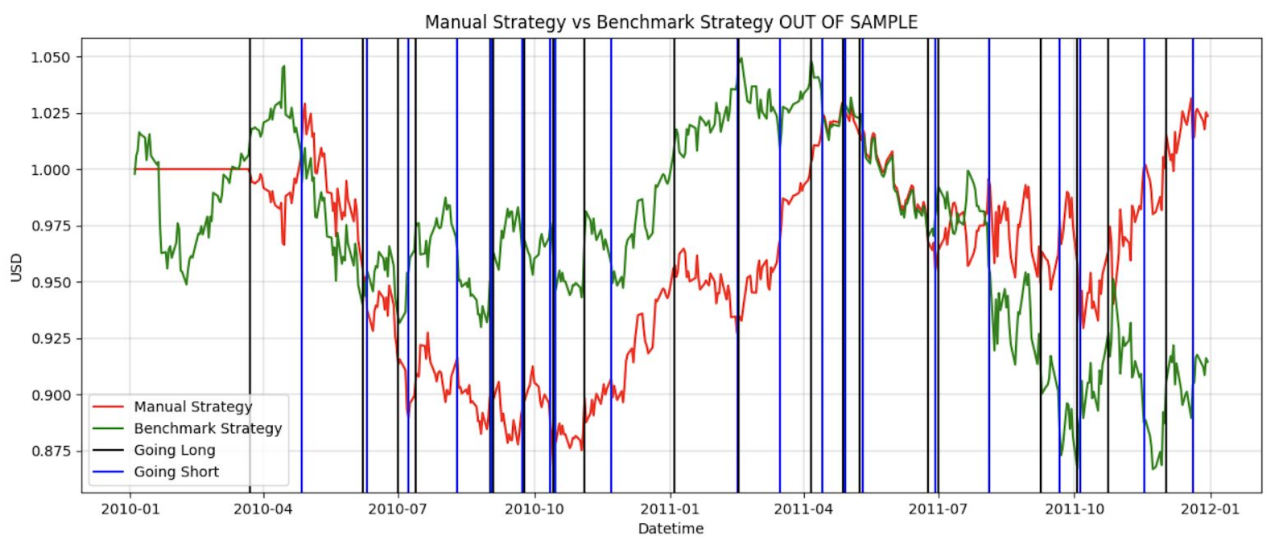
For each day in trading_range:
    If price is above or below ichimoku_cloud and yesterday_position != Out:
        If price_to_sma or bb_pos == Buy and yesterday_position != Long:
            If yesterday_position == Short:
                Enter a Long position (Buy 2000 shares of JP Morgan Chase and Co.)
            Else:
                Enter a Long position (Buy 1000 shares of JP Morgan Chase and Co.)
            yesterday_position = Long’
        Else If price_to_sma or bb_pos == Sell and yesterday_position != Short:
            If yesterday_position == Long:
                Enter a Short position (Sell 2000 shares of JP Morgan Chase and Co.)
            Else:
                Enter a short position (Sell 1000 shares of JP Morgan Chase and Co.)
            yesterday_position = Short

The results of this trading strategy can be seen in the graph below. From the moment that the manual strategy began to trade, its portfolio value almost never fell below that of the benchmark. Accordingly, the ending portfolio value was about $150,000 (~ 50% increase). Note: the symbol used in the graph below and all of the graphs in this paper is JPM (denoting the security of JP Morgan and Chase Co.)



Part IV: Comparative Analysis

The dataset used to “train” our Manual Strategy using technical analysis was for JP Morgan Chase and Co. (JPM) stock prices within the date range 01-01-2008 to 12-31-2009. As such to test how well our trading strategy would do on a testing set (out of sample: 01-01-2010 to 12-31-2011). The results can be seen in the graph below:



As you can see off the bat, the manual strategy performs much worse on the Out-of-Sample dataset than the prior In-Sample dataset. From the graph above, the maximum portfolio value that the manual strategy trader ends at is a little over $102,500 ($2,500 profit). Comparing this to our previous ending portfolio value of $150,000 ($50,000 profit) from our In-Sample dataset, the difference in performance is stark. Accordingly, whereas our In-Sample manual strategy trader showed an over steady increase in portfolio value, the Out-of-sample manual strategy trader shows neither a consistent overall increase or decrease in portfolio value, but oddly follows the trend of the benchmark strategy.

	Benchmark In-Sample	Manual In-Sample	Theoretically Optimal In-Sample	Benchmark Out-Sample	Manual Out-Sample	Theoretically Optimal Out-Sample
Cumulative Return	$1,232.49	$67,169.65	$578,610.00	-$8,357.91	$2,355.90	$312,020.00
Average Daily Return	$16.88	$107.76	$381.68	-$13.74	$7.81	$282.26
Std Dev of Daily Return	$1,704.12	$107.57	$454.78	$850.02	$798.81	$273.38

Accordingly, to look even further into the comparative performance, we can see in the chart above the overall comparisons between the Benchmark Strategy, Theoretically Optimal Strategy, and Manual Strategy both In-Sample and Out-of-Sample. While the manual in-sample strategy showed a cumulative return of $67,169.65 and a standard deviation of daily returns of $107.57, the manual out-of-sample strategy showed a cumulative return of $2,355.90 and a standard deviation of daily returns of $798.81. This indicates that not only did our manual strategy produce ~30x less return, but its returns on a daily basis are much more volatile, and thus less predictable (which is no help to our “strategy”). However, I would like to note though that because the date range chosen for the in-sample data set was during the crash of the housing market and financial crisis of 2008, our manual strategy may have been able to perform much better on this data set because its thresholds were tuned to periods of highly volatile prices. Accordingly, once markets began to stabilize, our manual trading strategy most likely did not perform as well because it could not capitalize on the same level of price fluctuations as it had before, and thus performed similarly to the benchmark (slightly better).