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DE LISBOA

# Volatility Based Trading Strategies

Bruno Miguel Vieira Rodrigues  
Master's Degree in Finance

Supervisor:

Pedro Manuel de Sousa Leite Inácio, Assistant Professor ISCTE-IUL,  
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November 2022



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## 2 Abstrato

O papel da volatilidade nos mercados está bem estabelecido ao longo dos anos. Como os traders tentam prever os movimentos de preços enquanto têm um rácio risco-recompensa adequado, os instrumentos baseados na volatilidade podem ser vistos como uma vantagem no arsenal de cada investidor para avaliar o risco.

O principal objectivo desta dissertação é criar e testar uma estratégia de negociação cujo objectivo é tentar prever e tirar partido dos movimentos voláteis dos preços das acções. Por conseguinte, antecipamos que a nossa estratégia produza maiores retornos quando comparada com a estratégia de holding

É importante notar que as ferramentas utilizadas para criar esta estratégia são apenas ferramentas disponíveis para a maioria dos investidores, uma vez que um dos objectivos desta dissertação é criar uma estratégia facilmente replicável que qualquer pessoa pode utilizar e aplicar relativamente ao valor nominal do investimento.

Nesta dissertação escolhemos uma amostra de prazos e diferentes activos, tais como índices e acções da Bolsa de Valores dos EUA, para testar a nossa estratégia por ser uma das escolhas mais populares dos investidores em todo o mundo, tendo mais liquidez.

Para a preparar, escolhemos três indicadores direccionais e outros cujo objectivo é tentar prever se haverá um movimento volátil de preços nas acções/índices a curto prazo. Para tal, o indicador Volatilidade Histórica será o principal indicador que permitirá ao trader tirar conclusões.

**Palavras-chave:** Trading; Mercado de Acções; Análise Técnica; Estratégia de Negociação; Estratégia baseada na Volatilidade.

### 3 Abstract

The role of volatility in the markets is well established throughout years. As traders try to predict price movements while having an adequate risk-reward, tools based on volatility can be seen as an advantage on the arsenal of every investor to evaluate risk in the market.

The main goal of this dissertation is to create and test a trading strategy whose goal is to try to predict and take advantage of volatile movements in stock prices. Hence, we anticipate that our strategy produces bigger returns when compared to the holding strategy

It is important to notice that the tools used to create this strategy are only tools which are available to the majority of retail investors, as one of the purposes of this dissertation is to create an easily replicable strategy that anyone can use and apply regarding the nominal value of the investment.

In this dissertation we have chosen a sample timeframe and different assets such as indexes and stocks from the US Stock Market to test our strategy for being one of the most popular choices from investors all over the world, gathering liquidity from it.

To prepare it, we have chosen three directional indicators and others whose goal is try to predict if there will be a volatile price movement in the stock/index in the short term. For this, the indicator Historical Volatility will be the main indicator that will allow the trader to take conclusions.

**Key-words:** Trading; Stock Market; Technical Analysis; Trading strategy; Volatility-based Strategy.

## 4 Introduction

Charles Henry Dow, the investor whose name was given to the American index “Dow Jones”, released what is known as the birth of Technical Analysis in 1884. A series of average closing prices of eleven companies whose goal was to understand the economic landscape of the United States of America and have a general macro-economic outlook.(Silva and Nunes, 2017, page 36)

In contrast, technical analysis evolved as a tool for investors whose goal is trying to predict future movements in price by studying past price behavior of a stock. Investors use it to evaluate their own decisions about investments and opportunities in the market to take advantage off, by maximizing their risk-to-reward ratio when entering a trade or simply finding opportunities to invest and predict their future returns.

Technical Analysis can be used exclusively by an investor or in a conjunction with other methods such as Fundamental Analysis. This type of analysis assumes that information is accessible to all investors and consequently it is already reflected in the price of a stock commodity, ETF or any other financial instrument (Hayes, 2021) , something that the theory that stock prices follow a “Random Walk” also agrees on.

This two approaches diverge on the fact that if stock prices follow an unknow path, consequently the study of past price action would be meaningless to predict any future stock price movement (Malkiel, 2015) (defended by Random Walk Theory) whereas Technical Analysis is simply the study of previous price action in order to try to predict future movements.

Technical Analysis is characterized by having a set of different ways to analyze price history. In essence, it has diverse tools such as various indicators, visual patterns observed in candlestick charts, point and figures charts, etc. When an investor uses it, he is searching for the best possible price entry either in a long or short position on a financial instrument and the best exit point in order to maximize profits and minimize the risk to which he is exposed when entering the trade.

Given the importance of volatility on the markets, topic that has been studied worldwide, the goal of this dissertation is to create a trading strategy that predicts and tries to maximize

profits from volatile periods on the market, in order to produce greater returns to investors when comparing this strategy to the standard one, the buy and hold strategy.

To address this issue, in this dissertation we will create a volatility squeeze-based trading strategy based on certain Technical Analysis indicators which will itself generate an indicator that gives oversold and overbought regions and consequently we can create trading rules with buy and sell signals.

Hence, after having the empirical results of our trading strategy using a large enough sample timeframe and a sample of different assets, we will compare its performance checking the validity of our trading strategy and its performance.

With the results obtained, we may conclude about the important role of volatility in a trading strategy to generate greater returns and the validity of Technical Analysis tools, as well as their applicability in real world trading strategies.

Lastly, given there are many different types of strategies traders use to outperform the market, this dissertation will verify if the idea of volatility breakouts is indeed a good way to implement a strategy or at least a good tool to have on the trading arsenal to a any trader.

Lastly, our dissertation will be structured in order to insure a reader that is not familiar with finance terms and knowledge still can apply the knowledge he/she will learn from this dissertation in the investments they will take in the future.

In Section 4, we will be reviewing the basics of Technical Analysis and the tools it can provide investors to take better informed decisions, as well as the critics and limitations of it, in order to ensure the reader can have a critic vision and create its own opinion towards the validation of what we are studying. On Section 5 we will be reviewing mostly concepts that are very present to every investor or trader and are necessary to comprehend for a better understanding of the reasonings of decisions that are take in our volatility-based strategy. On Section 6, the Methodology, we will understand how the process of creating the strategy will be unfold and on Section 7 we will discuss the data chosen and the timeframe where we will back test our strategy. On Section 8, we will study the results of our strategy when applied to the timeframe we have chosen and to the data, i.e. the stocks and assets that were discussed on Section 7. Finally, on Section 9 we will use Descriptive Analysis to study the significance of our trading strategy and ensure that it produces good results so it can be consider a good strategy, analyzing all the results and appreciations on the last Section, the Conclusion one.

## 5 Review of Literature

### 5.1 Assumptions of Technical Analysis

According to most of the authors on Technical Analysis, there are mainly three assumptions that are the base and fundament of the theory.

Firstly, every information is accounted in the price of a financial instrument, meaning that if investors have full access to information in the same way, the price of a stock at a certain moment in time has already discounted all the information available to investors.

Other essential assumption is that price follows a trend, in contrast with the idea that the returns generated are randomized. This trend is identifiable by observing past price action of the financial instrument and it is assumed that it will continue that same trend until a new one is formed.

Finally, technical analysis assumes that history repeats itself and that patterns often tend to repeat themselves, in either big time frames or small ones. This concept brings into consideration the market psychology and the human behavior surrounding it, although nowadays trading is dominated by automated bots and algorithms, that are created by humans.

### 5.2 Technical and Fundamental Analysis

When talking about analyzing a stock, traders and investors are mainly directed to technical and fundamental analysis, which are two opposite studies of stock but present themselves as two ways to analyze that could work in conjunction to create better and more informed decisions.

Fundamental Analysis consists in evaluating a stock by valuing it having into consideration its business, i.e. evaluating a company by having a look at the company's balance sheet, its earnings, the ability of the company to innovate or survive in case of a recession, if it is financially strong or not, by looking into financial indicators of a company...Fundamental



analysis has a longer-term view of a company, producing results if a company is doing well or not throughout the years.

Technical Analysis has more of a short to medium-term approaches to a stock, where traders try to identify good opportunities to take a position in it. Technical Analysis, in contrast with Fundamental Analysis, takes a look into price action of the stock, pattern repetition, indicators...meaning that in this type of analysis it does not matter the Company's outlook (balance sheet, future prospects...) as the theory defends that all those financial details are already reflected in the actual price of the stock. Usually, technical analysis is used by hedge funds in a time frame not longer than 6 months" (Fama and Blume, 1966).

### 5.3 Overview of Technical Indicators

To create our volatility-based strategy we will only use indicator only, not focusing our attention into visual patterns. These visual patterns can sometimes be interpreted differently by different traders and are more difficult to compute, hence there are significant statistical analysis problems on this last topic that still have to be solved (Griffioen, 2003, page 21).

The strategy will be based around volatility, and it consists in giving percentage weights on three different indicators, given the importance of each one of them. This only applies after having confirmation from the indicator Historical Volatility that we expect a volatility breakout, meaning that those three other indicators will be deciding on the direction we should predict the movement of the stock to take.

The first indicator to be used is the Money flow index indicator. This indicator is a momentum based-one and, in conjunction with the volume traded by a stock, it determines whether there is a market's momentum trending upwards or downwards.(Murphy, 2021). If the indicator assumes values above 80, one can say the stock is overbought, while if the indicator is below 20 it may indicate it is oversold.

To proceed to the calculations of the Money Flow Index, according to Investopedia (Mitchell, n.d.) :

$$Money\ Flow\ Index = 100 - \frac{100}{1 + Money\ Flow\ Ratio} \text{ where:} \quad (1)$$

$$\text{Money Flow Ratio} = 100 - \frac{14 \text{ Period Positive Money Flow}}{14 \text{ Period Negative Money Flow}}; \quad (2)$$

$$\text{Raw Money Flow} = \text{Typical Price} \times \text{Volume}; \quad (3)$$

$$\text{Typical Price} = \frac{\text{High} + \text{Low} + \text{Close}}{3}. \quad (4)$$

The second indicator to be used in our strategy will be “RSI”, Relative Strength Index. This one instead of being an indicator based on momentum like the previous one, is an oscillator whose values assumed are between 0 and 100. When the RSI assumes high values, it means that there were a lot of up movements and when it assumes low values it means there were a lot of down movements. Usually, traders assume a stock is undervalued if the RSI of a stock is below 30 and overvalued when RSI is larger than 70. Given this, we can create buy and sell signals on a stock (Silva and Nunes, 2017, page 98).

To calculate the value for the RSI we need to proceed into two steps (Fernando, 2021).

First, we must calculate the average percentage return generated during a period. The default period used is 14 periods, in which we will also use it in our strategy, since the majority of traders, as it is the default settings, use it.

$$RSI = 100 - \left[ \frac{100}{1 + \frac{\text{Average Gain}}{\text{Average Loss}}} \right] \quad (5)$$

After having collected the results for the number of periods that we want to calculate the RSI, in our case the 14 periods (days), to achieve the value of the indicator RSI we simply need to:

$$RSI = 100 - \left[ \frac{100}{1 + \frac{(\text{Previous Average Gain} \times 13) + \text{Current Gain}}{(\text{Previous Average Loss} \times 13) + \text{Current Loss}}} \right] \quad (6)$$

Like this, we achieved the RSI value for the 14 periods.

The last indicator of the three to create the directional part of our strategy are the Bollinger bands, created by John Bollinger.

It is characterized by being an envelope type of indicator. It appeals to the volatility of an asset using measures such as standard deviation to identify signals of buy or sell of an asset. The

touch of the upper band of the Bollinger bands indicator produces a sell signal and the touch of the price of the asset of the lower band produces a buy signal.

The indicator is composed by a line of the moving average of the prices of the asset and then two other lines (one upwards and one downwards) which are calculated by adding and subtracting the standard deviation to the moving average (Silva and Nunes, 2017, page195).

The upper line of the Bollinger Band is calculated by (Hayes, n.d.):

$$\text{Upper Band} = \text{Moving Average (Typical Price, } n) + m \times \sigma[\text{Typical Price, } n] \quad (7)$$

$$\text{Lower Band} = \text{Moving Average (Typical Price, } n) - m \times \sigma[\text{Typical Price, } n] \quad (8)$$

Where:

$$\text{Typical Price} = \frac{\text{High} + \text{Low} + \text{Close}}{3}; \quad (9)$$

$n$  = number of days in the smoothing period (the default number used is typically 20);

$m$  = number of standard deviations (default is typically 2);

$\sigma[\text{Typical Price, } n]$  = standard deviation over the last  $n$  periods of Typical Price;

$$\sigma = \text{standard deviation} = \sqrt{\frac{\sum_{i=1}^n (x_i - x_{avg})^2}{n-1}}; \quad x_{avg} \text{ is the mean of "x"}. \quad (10)$$

Finally, we have the last indicator used in the strategy, the Historical Volatility.

Historical Volatility measures at one point in time by how much an asset price is deviating from its average, meaning it can be deviating in upwards momentum or downwards (Chen, 2020). When the indicator is rising in value, it means that the price is moving directionally in a faster way than usual, while if it is dropping it means that the movement of price is returning to the "basis" (*Historical Volatility*, n.d.). This is an important factor to our strategy as when volatility is verified in the market, there are larger price movements, presenting like that an opportunity to have more profits.

To calculate the Historical Volatility, we simply want to calculate the 1-day historical volatility i.e. sample standard deviation of  $n$  daily logarithmic returns.

$$\sigma = \sqrt{\frac{\sum_{i=1}^n (R_i - R_{avg})^2}{n-1}}; \quad (11)$$

where:

$$R_n = \ln \left( \frac{C_n}{C_{n-1}} \right);$$

ln= natural log;  $C_n$ = Closing prices

$$R_{avg} = \frac{\sum_{i=1}^n R_i}{n};$$

Finally, the last step will be to annualize the historical volatility indicator's results, by multiplying the results achieved previously by the square root of 252, which is the average number of trading days in a year. Hence, we achieved the annualized historical volatility. (*Historical Volatility*, n.d.)

#### 5.4 Critics and limitations of Technical Analysis

Technical Analysis has had many critics over the years and there are not many studies made on the subject that address these limitations.

One of the main limitations pointed out by Technical Analysis skeptics is the fact that it is very subjective. As some technics such as chart reading rely on visual pattern recognition by traders, these are deemed as very subjective since one may vary of interpretation compared to other traders. The conclusions made by studies to address this situation are conflicting since opposite conclusions were made, remaining a good topic for future research. (Scott, Carr, n.d.) Given this subjectivity, there are difficulties academic studies show in properly testing how efficient is the use of Technical Analysis to generate greater returns for traders, being one of the main debated problems the data snooping. Data snooping happens when a researcher, in order to get his desired result (i.e. validation of his trading strategy, point of view...) searches for a database that will eventually validate his bias, meaning that the data set is chosen to validate a desired result (Griffioen, 2003).

Other critics are directed to indicators such as the Relative Strength Index or the MACD and others that are based on the price of the financial instrument. Given that, critics say that these are lagging indicators, meaning they produce buy and sell signals after the price movement that was expected already started, giving late entries on the positions a trader should take on a given financial instrument.

## 6 Important concepts

### 6.1 Money Management

According to (Silva and Nunes, 2017,page 25), to create an asset portfolio we should know beforehand what is our risk profile as an investor, for how long we are planning to have our funds invested and how much profit are we desiring. Only by knowing these details we can understand our profile as an investor, whether it is a risk averse profile or risk seeker one for example.

Important concepts such as risk tolerance, which refers to how much an investor or trader is willing to lose (potentially) in order to have potential profits, is important to have in mind and knowing this will allow the investor to understand in what financial asset to invest or the ones to avoid, whether it is riskier assets or simply risk free as the risk-free rate.

It is also very important to know for how long we are planning to hold the investment made and the necessity we have of that funds. If we have a big necessity of funds, we should expect the investment to be short-term instead of a long-term one. Also, when traders use leverage there are funding fees, that are simply fees collected by the broker due to the borrowing of money to the investor so he can use leverage, meaning that this could be a good tool for short-term trading but not for investing in the long-term.

Finally, every investor should have an idea of the profit he wants to make on his investment, which is related to his risk profile and the time he has his funds invested. Hence, an investor that tolerates more risk is able to have bigger profits than the risk averse investor.

After designing our investor profile, we should now pass to the search of financial assets that are suitable for us. Diversification is an important part of the process as with distributing our funds throughout different classes of financial assets we reduce the systemic risk that we are exposed to. Systemic risk simply refers to the risk that any investor is exposed to when entering the market, it is at risk in which is not related to the individual stock that the investor chooses

to put his/her money but rather the risk of the market itself as a whole. This could be seen as the possibility of a financial crisis where a company could be doing better than expected but due to that fact the stock probably decreases in price, large institutions defaulting leading to liquidations in stocks and investors turning into safe-haven assets rather than risk assets... simply put, systemic risk is the failure of the system itself rather than an individual company that makes part of it.

## 6.2 Leverage

When talking about trading or investments it is always important to mention some tools such as leverage. Leverage is when a trader borrows money from the broker/exchange so he can have more buying power to buy financial assets and in exchange he pays funding fees that work similarly to an interest rate. With more buying power comes more responsibility from the trader as the risk that he is exposed to is significantly bigger. Also, in leverage plays, the account's funds are used as collateral so the exchange guarantees their clients are able to pay the potential losses of their positions. Hence, stop-losses and risk management gain even more importance specially when in leveraged trades.

One general rule for investors is that it is not recommended to allocate more than 10% of the total funds in each trade, allowing some margin to add to the position in case bigger opportunities are given by the market(Silva and Nunes, 2017,page 29).

## 6.3 Risk-to-Reward Ratio

Risk-to-Reward Ratio concept is crucial to any trader, whether we are referring to a long-term investor or simply has a strategy of short-term trades.

This ratio divides the profit a trader will have in case the trade goes in his favor and hits his target price by the loss that will be assumed by the trader in case it goes on the other direction. Hence, the trader will know by looking at this ratio how much will he profit per every dollar/euro risked on the notional position of the trade.

The Risk-to-Reward Ratio is calculated simply by dividing the difference between the entry price and the stop-loss price by the difference of the profit target and the entry point.

$$\text{Risk - to - Reward Ratio} = \frac{\text{Price entry value} - \text{Stop loss value}}{\text{Price target of profit} - \text{Price entry value}}; \quad (12)$$

This ratio is particularly important due to the conclusions we as investors can take by understanding it, not only in a risk management way but also in a money management perspective.

If the ratio assumes values superior to one, it means that the risk is bigger than the potential reward, on the contrary, if it is less than 1, it means that the potential profit is greater than the potential loss (Milton, 2020).

Greater Risk-to-Reward ratios means that we can fail more trades and still be able to profit, for example, with 3 trades of same R:R ratio (3.5), if we invest the same amount in each trade and in four total trades we fail 3 but get 1 right, it means that we still make a 0.5 profit for every dollar invested (on the amount of each trade and not the total amount).

The relationship of the potential profit and potential loss is important since it translates to the trader if the profit potential is bigger than the loss potential or the contrary, leaving space for the trader to make a better decision based on it.

#### 6.4 Stop Losses and Profits

Stop-Loss orders are a fundamental tool used by traders and investors worldwide. They are an order placed by the trader to buy (if it is a short position) or sell (if it is a long position) an asset if it reaches a certain price during the trading hours and whose purpose is to ensure losses do not exceed what the trader initially decided to risk of his portfolio or even lock in profits on a try to “let profits run” and secure a minimum profit (Anderson, 2021).

It is especially important when traders use leverage on volatile environments, as with leverage, all the capital for a trader is in risk since it is given as collateral to leverage its positions.

## 6.5 Transaction Costs

Transaction costs are as the costs that incur to allow an economic exchange to be done (Black, Hashimzade and Myles, 2009).

In the purpose of this dissertation, the transaction costs are commissions and spreads paid to financial brokers such as exchanges for example. In case of a trader using leverage, there are also funding fees, which are commissions paid over the time the leveraged position is opened to the broker for the money borrowed above the notional size of the account of the trader.



## 7 Methodology

Firstly, we will compute the indicators in Matlab according to the description of each one of them and based on that, we create part of our strategy in Matlab as well.

Our strategy will be composed of two indicators. One will be an oscillator, whose values vary between zero and infinite. For values above 70 on our indicator we will consider a sell signal and when it reaches values equal or below 30 we consider a buy signal. This indicator will only be useful after we predict there will be a big movement on the historical volatility indicator. Our second indicator will allow us to predict those situations in which we are led to believe there will be volatility in the financial asset in specific.

First and foremost, we chose a volatility-based strategy since in theory, when there is a higher beta (risk) of any stock or portfolio of stocks, the higher should the return be to compensate investors given the higher risk, otherwise there would be no incentive to invest in high-risk stocks. The strategy that we are putting in place is riskier when compared to the buy-and-old since we are looking for volatile stocks and time periods, and instead of holding we have simply to follow our strategy and see what returns we can get.

For us, it is important to use the default settings of each indicator since these values are the ones that are pre-defined by most exchanges/brokers to use, hence most investors use them to define their one strategy.

As written in the book *“A Random Walk down Wall Street”* by Burton G. Malkiel, low volatility strategies can produce higher returns, especially in a long-term view, but can we produce even higher returns trying to predict volatility increases in stocks and their price directions? In practice, we are trying to predict when the volatility of a stock is low but increases, generating higher price moves and trying to profit from them.

Our strategy simply aims to take advantage of any big variation of prices of a stock in a way to find good entry and exit prices in order to increase the notional value of a trader’s account instead of taking a long-term approach of holding.

Hence, we expect that given that it is a higher risk associated with this strategy, then we expect a higher return and outperform the market by using some tools of Technical Analysis.

Given that we already have our four indicators that will compose our strategy chosen, we can now proceed to create our volatility-based strategy. For this, we will attribute weights to each indicator and then proceed to evaluate when the buy and sell signals are produced.

We will use statistics in order to test if our trading strategy is profitable and outperforms the buy and hold standard strategy, in specific the statistical tests known as “t-tests”.

The hypothesis to be studied are the following:

- 1) The returns generated by our strategy (Model A and B) are significantly different from zero

Given a  $\alpha$  level of confidence, if the value of the t-statistic is in absolute value bigger than the critical value related to the level of confidence chosen, we reject the null hypothesis.

- 2) The returns generated by the sell signals are negative

Since we are comparing it to a buy and hold strategy, the most important part is to understand if the sell signals generated by our strategy generate negative returns to holders during the period until the next buy signal, i.e. when we have no position in the asset. If they do so, it means that this trading strategy is outperforming the holding one.

Finally, our volatility-based strategy will produce two different Models, Model A and B.

Simply put, Model B has the same fundamentals as Model A as everything is the same besides the fact that Model B produces more signals since it does not have trades not being done because of the ‘trendvs’ indicator, whose purpose is to check if there are good conditions that would allow us to have good results given the type of position we wanted to open (long or short).

While in Model A there is a buy signal produced by the column ‘Type’, it is only valid if the ‘trendvs’ indicator equals to zero (since being equal to zero we consider to be good for long

positions) or for shorts, if the signal is 'Sell' we only enter the position if 'trendvs' indicator is equal to 1, in Model B this type of filtering does not happen, meaning that we will have the same trades executed in Model A plus the ones rejected by the filter of the 'trendvs'.

### **Process step-by-step**

-We will take a position on the stock (long or short), so it is a price directional strategy.

-Volatility indicators will help us by identifying moments where volatility was low and is growing, so that bigger changes in the price of the stock are more likely and we can produce bigger returns for our investments, as well as having in mind that there is more risk involved.

-Money Flow Index will allow us to understand if it exists any trend or momentum on the stock so that the position we will afterwards assume will be in syntony with this trend, while the indicator Historical Volatility will tell us how fast are these directional changes in price happening and will help us understand if we should expect bigger changes in the price of the stock in the short term.

-Finally, the Relative Strength Index and Bollinger Bands produce buy and sell signals, so we can understand in a better way if it is a good strategy to enter on a trade by assessing these two indicators.

-How to identify Stop loss prices and stop profits? We will use the metrics generated by the Risk-to-Reward ratio, under which we define the maximum percentage we are willing to lose in a trade and based on a Risk-to-Reward ratio we define the profit target. An appropriate Risk-Reward ratio must be chosen in order to create a good trading strategy.

-To enter in a trade, we will identify the trend by subtracting the price of the stock by its price one week early and 1 month early and take a position based on the trend.

-While the RSI and Bollinger bands are expected to give us buy and sell signals, we will use money flow index to reassure the trend and give us an outlook of the volume traded by the stock, meaning more interest on it. Historical volatility will show us if we should expect a big move for the stock or not, and we will only enter the trade if in fact we are expecting a big move that will generate greater returns potentially.

-To check if this strategy is good, we will compare the results with the results obtained by the “Buy and Hold” Strategy. At first sight, we should definitely expect bigger returns since it is a volatility-based strategy, meaning that if there is more risk involved it should have bigger potential profits as well, to compensate that risk assumed by the trader.

## 8 Data

To proceed to the testing necessary to our strategy in a way to evaluate either the strategy is a good one or not, we will choose a sample period and compare the strategy's results, of both Models (A and B) with the results of the buy and hold strategy, which is the standard one.

We will choose 5 different stocks and an index to test out the performance of our Models.

The first stock to be chosen is Tesla (ticker: \$TSLA) which can be considered as one of the American stocks that is very volatile as its price variations are bigger when compared to most of the stocks that constitute American indexes (DOW JONES, S&P 500...) and it fulfills our criteria as it has both liquidity and enough volume that allow us to trade without worrying about big price variations caused by our trade notional size.

The other four companies chosen to be in our sample were Advanced Micro Devices Inc. (ticker: \$AMD), NetFlix Inc. (ticker: \$NFLX), Alibaba Group Holding Ltd. (ticker: \$BABA) and finally Simon Property Group Inc. (ticker: \$SPG). All of these stocks are listed on the NYSE, the American stock exchange, and were chosen to have a sample of some growth stocks to give us a better idea if the strategy was able to capture and profit from the big variations some of them had.

We retrieved daily data of the stock using the website *Finance.Yahoo* during a sample period big enough that allow us to properly test our strategy and take conclusions from it, in which it will be a five-year period. Finally, we will retrieve data from the index S&P 500 using its ETF Trust, \$SPY to do so for our testing using indexes.

Since our goal is only to test the performance of our strategy and compare it to the buy and hold strategy, it is not interesting to proceed to considerations as risk free investment or any other investment in different currencies, like this we eliminate variables not so interesting to our purpose.

Due to a limitation of the data acquired, the timeframe of the 5 years in the stocks may differ the start date in a matter of a day between them, around the period of 06/04/17, which does not make any difference for our purpose to test the performance of our Strategy.

For the index S&P 500 the timeframe chosen differs from the others since in the same timeframe the signals our strategy provided were in fact very low due to the fact that the financial instrument, by being an index, implies less volatility and to try to evaluate its performance we then considered increasing the timeframe an adequate solution. To solve this issue, we decided to analyze an extended timeframe when compared to the others (19 years compared to 5years).

## **8.1 Stock choice Criteria**

### **8.1.1 Liquidity**

To understand the concept of liquidity, it is crucial to first understand what are the bid and ask prices.

The “bid price is “the price at which someone is willing to buy a certain stock or financial asset and has an order placed to do so. On the other hand, the “ask price is “the price at which someone who holds the asset is willing to sell it. The bid price is always lower than the ask price as if it was higher than the transaction would have already taken place. The difference between the bid and ask price is called the “bid-ask spread”, which is one direct indicator of the liquidity of the financial asset. The tinier this spread, the more liquid an instrument is, meaning that for our strategy, as liquidity is one of our criteria, we should go with the ones that have a tinier “bid-ask spread” (Silva and Nunes, 2017, page 52). Large “bid-ask spreads” cause a bigger price variation to open and close a position on that asset, meaning an investor should demand higher returns when investing in these low liquidity assets when compared to higher liquidity investments.

### **8.1.2 Volume**

Volume is an indicator that allows investors to know what was the number of shares traded, i.e. exchanged by investors/traders, during a given time horizon. It is used by the majority of traders to identify how strong price moves are and identify trends in the price action. According to Burton Malkiel, the author of the book “*A Random Walk Down Wall Street*”, there are Price-Volume systems that propose the following:

On one hand, when a stock price increases on increasing volume, we can conclude that it exists an excess number of buyers, leading us to logically think that the stock will continue to increase in price. On the other hand, if a stock price falls while it is registered larger volumes compared to the ones traded usually, selling pressure is bigger than buying pressure and the price of the stock should continue to decrease. (Malkiel, 2015, page 109).

Finally, it is expected that a stock with higher volume during a sample period is more liquid than stocks with lower volume.

## 9 Empirical results

### 9.1 Assumptions

- No leverage will be used;

- Zero funding fees for short positions open;

- Spread of 0.125% on each transaction, that is, since a trade will have only 2 transactions then 0.25% spread for each trade to have into account liquidity and price effects of our transaction orders. (also to consider transaction costs);

- Buy and hold positions are simply a long opened at the beginning of our sample period and liquidate positions on the last day of the period;

- No positions will be held open in the end of the sample period, all of them will be liquidated even if there is no signal to do that;

- Risk Management only applies to Closing prices and not to prices that could be seen during the trading opening hours of the day, meaning that a stock could hit a Stop Loss price as many times as possible, but if it closes above that price (in a long position), then no action will be done.

### 9.2 Spreads

As stated previously in the previous Assumptions section, when back testing our Models, we will use a 0.125% spread on the price of the stocks and indices for each transaction. Thus, since the trades we will execute are composed by only 2 transactions, one to open the position and another to close it, each trade will have a spread of 0.25% embedded in the result of it. It is also important to notice that for simplicity reasons we will ignore the fact that in most exchanges, to open short positions on a financial instrument, a funding fee exists related to the time that we keep the position open.



### 9.3 Risk-to-Reward Ratio

Table 1- Trading Strategy statistics

<b>Count Longs</b>	<b>259</b>
<b>Count Shorts</b>	<b>62</b>
<b>Count Stop Losses hi</b>	<b>23</b>
<b>Count Stop Profits</b>	<b>4</b>

Table 2- Number of trades

<b>Trades open</b>	<b>321</b>
<b>% Stop Losses hit</b>	<b>7.17%</b>
<b>% Profit Targets hit</b>	<b>1.25%</b>

Source: Bruno Rodrigues

One thing to have into attention on our Models is the risk management, that is, the risk-to-reward ratio. A Risk-to-Reward ratio of 2.5 means that by entering a trade we are risking 1 monetary unit to win 2.5 for every monetary unit invested.

By using a 2.5 Risk-to-Reward ratio, we can see that in 321 trades, only four hit the targets and about twenty-three were losing trades (hit the Stop losses).

Those results show us that the Stop Losses were hit about six times more (5.76x) than the Targets, which is a very bad result given the Risk to Reward ratio is 2.5.

The targets are simply made by having a criteria Stop Loss and multiplying it by the ratio.

Table 3- Risk-to-Reward Ratios chosen

9	Risk	R:r	Targets
<b>Longs</b>	15.00%	<b>2.5</b>	37.50%
<b>Shorts</b>	10.00%	<b>2.5</b>	25.00%

Source: Bruno Rodrigues

## 10 Descriptive Analysis

In this section we will use descriptive analysis to research about the statistical significance of our strategy and consequently models and their profitability.

For this, we will make use of the 'T-Test', which is a statistical test whose t-statistic follows a Student t-distribution and is used to compare the means of two samples.

With this method is possible to test a hypothesis and find if there is any statistical significance to what we are inferring from. In our case, as we want to compare it with a mean equal to zero, we will use a Dummy variable to proceed the test using Excel's Data function "*T-Test using unequal variance*".

Given that, we will be able to take conclusions about our Models, compare it's results and see if it happens to be a good alternative to the standard strategy of buy and hold.

Before proceeding to analyze the results given by the t-tests, it is important to have in mind that our strategy produces a relatively small sample of number of observations, especially in Model A. Having that into account any result given by the t-test and consequently any interpretation is going to be seen with a skeptic eye since a small sample may deviate results and not show the reality with efficacy.

For the tests, and in case of not being mentioned, we will use the standard alfa 0.05 that is used as a general standard on majority of t-Tests, that is, the significance level used in the following t-tests will be of 95%.

In our strategy we will have two models, Model A and B, in which the Model B is simply the strategy of the Model A but with less filtering, allowing us to have a bigger number of trades during the same sample period studied and consequently will give us a better insight into what this strategy can produce.

## 10.1 Initial strategy

To initiate the study of our strategy's statistical significance, we first looked at the returns generated by each trade and applied the study the T-tests to find if they were statistically significant, which they were not.

Table 4- Results of studying the Returns of the Model A

		<b><i>Done in % With spread- Model A</i></b>
Mean		0.936%
Variance		1.733%
Observations		53
Hypothesized	Mean	
Difference		0
df		52
t Stat		0.51741491
P(T<=t) one-tail		0.30353036
t Critical one-tail		1.67468915
P(T<=t) two-tail		0.60706072
t Critical two-tail		2.00664681

Source: Bruno Rodrigues

Table 5-- Results of studying the Returns of the Model B

	<b>Done in % With spread- Model B</b>
Mean	0.244%
Variance	0.598%
Observations	268
Hypothesized	Mean
Difference	0
df	267
t Stat	0.51631533
P(T<=t) one-tail	0.30303077
t Critical one-tail	1.6505806
P(T<=t) two-tail	0.60606153
t Critical two-tail	1.96888862

Source: Bruno Rodrigues

As we can observe by the results of the T-tests applied to each model individually, the p-value were about 0.5 and 0.6, far superior to the alfa used to the study of the significance of the trading strategy, which was 0.5.

Given this, we would conclude that the returns were not statistically different from zero and due to that our strategy and Models were shown to not be good and our dissertation had failed to create a good trading strategy. Hence, the solution that allowed us to keep studying it and to get statistically significant results were simply change the returns by the price variation as the variable of study. Instead of looking at the returns of each trade, we will focus on the price variation given by each trade, that is, independent of the type of position we take (short or long), we will only consider the initial and final price of the financial asset to analyze, meaning that we are studying the price variations given by each signal produced by our strategy. With this small change, it was possible to obtain results that were significantly different from zero and with that we were able to advance in our study.

The first hypothesis to be evaluated will be:

H0: Price variation generated by signals (buy and sell) is statistically different from zero.

H1: Price variation generated by signals (buy and sell) is no statistically different from zero.

Table 6- Results of studying the Price Variations of Both Models

	<i>Done in % With spread-Both Models</i>
Mean	1.141%
Variance	0.769%
Observations	321
Hypothesized Mean Difference	0
df	320
t Stat	<b>2.330673341</b>
P(T<=t) one-tail	0.010195825
t Critical one-tail	1.649629305
P(T<=t) two-tail	<b>0.020391649</b>
t Critical two-tail	<b>1.967404974</b>

Source: Bruno Rodrigues

By looking at the results of the buy and sell signals generated by both models in conjunction, we will try to understand if this strategy is statistically different from zero and consequently produces good or bad results. After, we will proceed to analyze it model by model.

First and foremost, it is important to highlight that this t-Test was made at a 95% confidence level. We observe that the p-value (0.020391649) generated by the t-test is inferior to the alfa used (0.05), thus we end up not rejecting the null hypothesis. An important notice in the study of the significancy of the trading strategy is that the p-value in question that we shall take into consideration is the two-tail as the distribution of the T-test is a two-tailed T-student.

By not rejecting the null hypothesis, we can conclude there is no statistical evidence to support that the alternative hypothesis is correct, meaning that the returns generated by the signals might be different than zero, producing positive or negative returns at a 95% confidence level and given this sample.

Although until this moment the volatility based strategy can sound promising, when looking at the price variations generated model by model and applying the T-test to both of them isolated, instead of looking at the price variations of Model A and B in conjunction, we can conclude that the t-statistic of both T-Tests end up in the Rejection Area of the two-tailed distribution, thus resulting in a rejection of the null hypothesis and consequently the alternative hypothesis being considered correct given this sample and for a 95% confidence level. This means that for an alfa of 0.05, the returns generated by each model are not considered statistically different from zero.

#### Results:

Table 7-Results of studying the Price Variations of Model A

	<i>Done in % With spread- Model A</i>
Mean	2.78%
Variance	1.66%
Observations	53
Hypothesized Mean Difference	0
df	52
t Stat	<b>1.569091641</b>
P(T<=t) one-tail	0.061346157
t Critical one-tail	1.674689154
P(T<=t) two-tail	<b>0.122692314</b>
t Critical two-tail	2.006646805

Source: Bruno Rodrigues

	<i>Done in % With spread- Model B</i>
Mean	0.008168076
Variance	0.005915562
Observations	268
Hypothesized Mean Difference	0
df	267
t Stat	<b>1.738557893</b>
P(T<=t) one-tail	0.041632643
t Critical one-tail	1.650580601
P(T<=t) two-tail	<b>0.083265286</b>
t Critical two-tail	1.968888622

*Source: Bruno Rodrigues*

What can explain this situation? Essentially, and to emphasize, each model has a relatively small sample of number of observations. Having that into account any result given by the t-test is going to be seen with a skeptic eye. A 95% confidence level, although seen as the standard confidence level, can be considered high. When we increase the alfa to 0.15, thus decreasing the confidence level to 85%, we observe that we no longer reject the null hypothesis, so we can conclude that at an 85% confidence level, each model (A and B) produces results statistically different from zero.

With alfa= 0.15:

Table 8- Results of studying the Price Variations of Model A and B

		<i>Done in % With spread- Model A</i>
Mean		0.027798
Variance		0.016634
Observations		53
Hypothesized	Mean	
Difference		0
df		52
t Stat		<b>1.569092</b>
P(T<=t) one-tail		0.061346
t Critical one-tail		1.046873
P(T<=t) two-tail		<b>0.122692</b>
t Critical two-tail		1.461117

Source: Bruno Rodrigues

		<i>Done in % With spread- Model B</i>
Mean		0.008168
Variance		0.005916
Observations		268
Hypothesized	Mean	
Difference		0
df		267
t Stat		<b>1.738558</b>
P(T<=t) one-tail		0.041633
t Critical one-tail		1.03845
P(T<=t) two-tail		<b>0.083265</b>
t Critical two-tail		1.443685

Source: Bruno Rodrigues



Hypothesis number two:

H0: Price variations generated by sell signals are negative.

H1: Price variations generated by sell signals are not negative.

Table 9- Results of studying the Price Variations of the trades we enter as short positions

	<i>Shorts Done in % to both Models with spread</i>
Mean	<b>2.03%</b>
Variance	<b>0.24%</b>
Observations	62
Hypothesized Mean Difference	0
Df	61
t Stat	<b>3.261458</b>
P(T<=t) one-tail	0.000908
t Critical one-tail	1.670219
P(T<=t) two-tail	<b>0.001817</b>
t Critical two-tail	1.999624

Source: Bruno Rodrigues

By analyzing the short signals isolated from each model, we can verify that in both Models (A and B) we conclude that the price variations generated by the trades are statistically different from zero. Also, in both models we conclude that the returns are actually positive by looking at the mean and variance, which in a short position it means we incur in a loss, given that we are studying the price variations that occur after we enter a trade. This analysis allow us to understand that the short positions taken during the timeframe considered in the back testing actually decreased the profitability of both Models and consequently our strategy.

Results:

Table 10-Results of studying the Price Variations of the trades we enter as short positions in Model A

	<i>Shorts Done in % With spread- Model A</i>
Mean	<b>4.072%</b>
Variance	<b>0.205%</b>
Observations	12
Hypothesized Mean Difference	0
df	11
t Stat	<b>3.118496239</b>
P(T<=t) one-tail	0.004888088
t Critical one-tail	1.795884819
P(T<=t) two-tail	<b>0.009776176</b>
t Critical two-tail	2.20098516

Source: Bruno Rodrigues

Table 11-Results of studying the Price Variations of the trades we enter as short positions in Model B

	<i>Shorts Done in % With spread- Model B</i>
Mean	<b>1.536%</b>
Variance	<b>0.239%</b>
Observations	50
Hypothesized Mean Difference	0
df	49
t Stat	<b>2.219398</b>
P(T<=t) one-tail	0.01556
t Critical one-tail	1.676551
P(T<=t) two-tail	<b>0.03112</b>
t Critical two-tail	2.009575

Source: Bruno Rodrigues

How can we explain this? This situation can be explained by the fact that as we defined previously, this strategy is short positions averse, given that in the long run, the tendency for a stock is to increase in price. Thus, we translate this situation into a stricter risk management by using a stop loss of 10% compared to the 15% used in Longs positions. Since the stop loss is tighter in shorts, it can be seen as normal to have a bigger number of observations of stop losses hit in short positions rather than in long positions, especially in a volatile environment like the one we tend to take advantage of.

## 10.2 Trading Strategy Results

By looking at the table of the comparison of our strategy (Model A and B) to the buy and hold strategy, we can verify that in these 5 stocks chosen, our strategy outperformed the standard strategy when the stocks had a bad performance over the given period (BABA and SPG), suggesting it to be a good strategy in periods of recession. On the contrary, we can clearly verify that the buy and hold strategy outperforms by far our models when the stocks had an immense growth, such as AMD and TSLA for example.

Given this, we are led to believe that our volatility based strategy is more successful in stocks that do not do well in the long run and might be good to use during bear markets and recession times, which in theory makes sense given that volatility is higher during rough market conditions leading to our strategy to have more trades, situation that can explain a possible outperformance given that in our strategy we want to capitalize on volatility and in the periods where stocks lose the most.

Table 12- Results in percentage of the Models

	Model A	Model B	Buy & Hold
AMD	24.665%	-9.532%	704.974%
		-	
TSLA	26.510%	16.222%	2037.232%
BABA	15.813%	44.857%	0.657%
NFLX	9.413%	33.178%	156.680%
	-		
SPY	21.352%	-6.393%	301.888%
SPG	-4.133%	8.066%	-24.704%

Mean	8.486%	8.992%
Variance	3.38%	6.18%
Sum		
returns	50.916%	53.954%

Source: Bruno Rodrigues

Strategy results with spreads considered in each trade:

Table 13- Results in percentage of the Models taken into account a spread of 0.125% in each transaction

	Model A	Model B	Buy & Hold
AMD	24.465%	7.758%	704.974%
		-	
TSLA	26.360%	16.647%	2037.232%
BABA	15.663%	44.157%	0.657%
NFLX	9.263%	32.503%	156.680%
	-		
SPY	21.852%	-9.518%	301.888%
SPG	-4.308%	7.091%	-24.704%

Mean	8.265%	10.891%
Variance	3.42%	5.55%
Sum		
returns	49.591%	65.344%

Source: Bruno Rodrigues

When comparing both Model A and B, first and foremost is important to notice what differs between them. As said previously, Model B is the same as Model A but with less ‘filters’ that allow us to have a bigger number of signals and consequently trades within the same time period. With this in mind, we will now proceed to study the efficiency of the strategy’s signals.

By comparing both Models, we can verify that Model B outperforms Model A in stocks that Model A outperforms the buy and hold standard strategy and underperforms in 2 out of 4 stocks where Model A underperforms the standard strategy. Thus, is it fair to say that Model B is a better version of Model A? Looking at this sample of stocks and given this timeframe for the analysis, the mean of the returns generated by the Model B is slightly higher than Model A (8.992% compared to 8.486%) while the variance of Model B is about double the variance of Model A (6.18% compared to 3.38%), suggesting that the returns from Model B are more volatile than Model A.

#### Studying the strategy without money management associated to it:

By taking out the days in which the stop losses or target prices were exercised we are simply observing how the strategy unfolds during this sample period without the risk management associated to it. Also, it is important to note that by taking these days out we are eliminating the days in which volatility was higher, since stop losses and price targets are ceiling prices for the strategy itself.

With the results of the t-test we can see the strategy is statistically different from zero given this sample period and for this sample at a 95% confidence level. And it produces a return in average of 1.52% in each trade.” This situation goes in contrast with the fact that analyzing the full strategy, that is, having the same sample of trades plus those in which stop losses and targets are hit, also with an alpha of 0.05, we reject the null hypothesis.

Table 14

		<i>Done in % with spreads</i>
Mean		<b>1.52%</b>
Variance		<b>0.51%</b>
Observations		294
Hypothesized	Mean	
Difference		0
df		293
t Stat		<b>3.646448</b>
P(T<=t) one-tail		0.000157
t Critical one-tail		1.650071
P(T<=t) two-tail		<b>0.000315</b>
t Critical two-tail		1.968093

Source: Bruno Rodrigues

## 11 Conclusion

Looking at our results, it is verifiable that we were able to create a volatility-based strategy easily replicable by any retail investor, as it was intended. Given that our strategy produced results statistically different from zero and ended up being positive returns, we could say that this strategy could be further developed to gather more information and consequently produce better results.

With this, we can speculate more about the role of volatility in the markets and how can it be considered into different trading strategies.

As we have seen previously the important role of volatility in the markets, volatility-based strategies present to be a good subject for further analysis and development and are subject to the general understanding of the creator's developer.

Finally, and as a suggestion for further research, it would be interesting to study how tools like the VIX and other macro environmental variables such as 10y US rates or price of oil to create a in-depth model that could represent a better understanding of macroeconomic risk factors and retrieve even better trading results given it is not focused only on one financial asset and has the environmental aspect of it taken into account.







v\$ value		trends		dte		Enter position		Du		Trends		Type		Final		Closing prices		Fecha da posicao		Close Price		Done in %		SL Price		SL HIT?		SL % made		TESTE	
vs value at dte	Date	Minimum days between signals	Close prices at dte	Type of position	Date	trends	Type	Final	Closing prices	Fecha da posicao	Close Price	Done in %	SL Price	SL HIT?	SL % made	TGT Price	TGT HIT?	TGT MADE %													
0	15	38	40.82405006	Buy	26/04/2017	0	Buy	Buy	165.039993	24/05/2017	159.78	-3.187%	140.284	0	226.93	0	226.93	0													
34.35635	0	40	61.78272526	Buy	30/05/2017	0	Buy	Buy	154.979996	27/06/2017	162.37	4.768%	131.733	0	213.0975	0	213.0975	0													
44.55534	1	94	51.87334175	Buy	29/06/2017	0	Buy	Buy	162.580002	28/07/2017	166.52	-1.267%	136.195	0	223.5475	0	223.5475	0													
54.79991	0	116	50.66774345	Buy	17/08/2017	0	Buy	Buy	157.199997	15/09/2017	164.77	4.816%	133.62	0	216.15	0	216.15	0													
47.4645	0	138	52.01908489	Buy	19/09/2017	0	Buy	Buy	159.729996	17/10/2017	167.10001	4.614%	135.7705	0	219.6287	0	219.6287	0													
50.40386	0	161	54.54164179	Buy	19/10/2017	0	Buy	Buy	165.520004	16/11/2017	159.87	-3.413%	140.692	0	227.59	0	227.59	0													
54.88976	0	185	62.0440906	Buy	21/11/2017	0	Buy	Buy	159.149994	20/12/2017	163.198	3.055%	135.2775	0	218.8312	0	218.8312	0													
45.78453	1	205	35.52810052	Buy	27/12/2017	0	Buy	Buy	170.770004	26/01/2018	163.71001	-4.134%	145.1545	0	234.8088	0	234.8088	0													
52.70481	1	235	48.84659371	Buy	26/01/2018	0	Buy	Buy	167.710007	26/02/2018	159.07001	-2.846%	139.1535	0	225.1013	0	225.1013	0													
52.05413	0	259	51.86038114	Buy	12/03/2018	0	Buy	Buy	156.740005	10/04/2018	154.929999	-1.155%	133.229	0	215.5175	0	215.5175	0													
50.29793	1	281	64.75034994	Buy	16/04/2018	0	Buy	Buy	152.279999	14/05/2018	158.02	3.769%	129.438	0	209.385	0	209.385	0													
36.65831	1	302	65.98207729	Buy	16/05/2018	0	Buy	Buy	154.309998	14/06/2018	164.05	6.312%	131.1635	0	212.1762	0	212.1762	0													
57.28886	1	322	56.75090485	Buy	15/06/2018	0	Buy	Buy	164.479996	16/07/2018	170.166	3.727%	139.806	0	226.16	0	226.16	0													
66.39398	1	344	59.67995028	Buy	16/07/2018	0	Buy	Buy	170.660004	13/08/2018	174.78999	2.420%	145.061	0	234.6575	0	234.6575	0													
51.52382	0	366	49.49414829	Buy	15/08/2018	0	Buy	Buy	177.139999	13/09/2018	181.56	2.495%	150.569	0	243.5675	0	243.5675	0													
35.5281	2	388	49.03287588	Buy	17/09/2018	0	Buy	Buy	182.460007	15/10/2018	178.64	-3.717%	155.941	0	252.2575	0	252.2575	0													
42.04094	0	410	59.8197688	Buy	17/10/2018	0	Buy	Buy	172.75	14/11/2018	183.52	6.234%	146.8375	0	237.5313	0	237.5313	0													
39.03978	0	446	63.7153784	Buy	16/11/2018	0	Buy	Buy	185.070007	18/12/2018	186.95	1.016%	157.3095	0	254.4713	0	254.4713	0													
46.27849	0	466	61.86594618	Buy	11/01/2019	0	Buy	Buy	172.350006	11/02/2019	178.5	3.568%	146.4975	0	236.9813	0	236.9813	0													
40.40211	1	487	39.59099618	Buy	11/02/2019	0	Buy	Buy	185.300003	12/03/2019	183.28	-1.090%	157.505	0	254.7875	0	254.7875	0													
54.6906	1	509	70.5298622	Buy	13/03/2019	0	Buy	Buy	178.139999	10/04/2019	181.11	1.667%	151.419	0	244.9425	0	244.9425	0													
68.72853	1	529	38.84473704	Buy	12/04/2019	0	Buy	Sell	185.200004	29/04/2019	175.75	-5.599%	204.072	0	189.14	0	189.14	0													
51.61687	1	551	33.39066826	Buy	13/05/2019	0	Buy	Buy	175	11/06/2019	168.00	-3.849%	148.75	0	240.625	0	240.625	0													
59.1188	0	572	46.32655913	Buy	13/06/2019	0	Buy	Buy	163.820007	12/07/2019	159.92999	-2.375%	139.247	0	225.2525	0	225.2525	0													
53.84986	0	598	40.3046405	Buy	15/07/2019	0	Buy	Buy	162.600006	12/08/2019	159.84	-1.820%	138.21	0	223.575	0	223.575	0													
51.30144	0	624	51.58822871	Buy	20/08/2019	0	Buy	Buy	147.520004	18/09/2019	150.14999	1.783%	129.392	0	202.84	0	202.84	0													
59.48399	0	646	71.59964615	Buy	26/09/2019	0	Buy	Buy	155.619995	24/10/2019	147.19	-5.417%	132.277	0	213.9775	0	213.9775	0													
65.48301	0	668	41.55371986	Buy	28/10/2019	0	Buy	Sell	153.839996	11/11/2019	155.42	-1.017%	169.224	0	115.38	0	115.38	0													
37.48282	1	688	56.45915736	Buy	27/11/2019	0	Buy	Buy	147.520004	28/09/2019	150.14999	1.783%	129.392	0	202.84	0	202.84	0													
44.03239	0	708	43.10252387	Buy	27/12/2019	0	Buy	Buy	147.589996	28/01/2020	145.28999	-1.058%	125.4515	0	202.9362	0	202.9362	0													
51.08532	1	722	60.51114544	Buy	28/01/2020	0	Buy	Buy	139.990005	26/02/2020	142.08	1.493%	118.9915	0	192.4863	0	192.4863	0													
51.64187	0	745	48.43063495	Buy	27/02/2020	0	Buy	Buy	113.379997	11/05/2021	122.36	7.920%	96.373	0	155.8975	0	155.8975	0													
79.30715	1	1072	44.55052808	Buy	28/05/2021	0	Buy	Buy	128.490005	28/06/2021	133.28	3.728%	109.2165	0	176.6738	0	176.6738	0													
56.76744	1	1104	50.18217608	Buy	08/07/2021	0	Buy	Buy	125.089996	05/08/2021	125.1	0.008%	106.3265	0	171.9987	0	171.9987	0													
52.21491	0	1151	76.50378301	Buy	23/08/2021	0	Buy	Buy	129.460007	21/09/2021	134.58	3.965%	110.041	0	176.0075	0	176.0075	0													
46.72391	1	1201	66.43678426	Buy	27/09/2021	0	Buy	Buy	134.149994	25/10/2021	132.62	-1.141%	114.0275	0	184.4562	0	184.4562	0													
42.72586	0	1252	50.10120022	Buy	28/10/2021	0	Buy	Sell	147.119995	11/11/2021	165.44	-11.07%	161.832	7	-11.50%	110.34	0	110.34	0												
			24/03/2022	Buy	10/01/2022	0	Buy	Buy	160.880005	08/02/2022	146.78	-8.764%	136.748	0	221.21	0	221.21	0													
			24/03/2022	Buy	24/03/2022	0	Buy	Buy	130.130005	00/01/1900	127.86	-1.744%	110.6105	0	178.9288	0	178.9288	0													

Ticker: \$SPY



## **Most important codes used in Matlab:**

### **To construct the “trendvs” indicator:**

```
function trend= trendvs(MFI,period,vs)
positionlist=[]
for i = period+1:length(MFI)

    if vs(i)-vs(i-1) < vs(i-1)-vs(i-2) < vs(i-2)-vs(i-3) % is good for selling, indicator is decreasing faster

        positionlist(end+1)= 1; % 1 is good for selling
    elseif vs(i)-vs(i-1) > vs(i-1)-vs(i-2) > vs(i-2)-vs(i-3) % is good for buying,indicator is growing
    Faster

        positionlist(end+1)= 0
    else
        positionlist(end+1)= 2
    end
end

end

trend= positionlist
end
```

### **To construct the “vsvalue” indicator:**

```
function vs= Volsqueeze(RSI,MFI,Excel,upper,middle,lower)
vs=[];
period=14;
for i = period+1:length(MFI) %começa porque RSI nao tem valores antes e acaba porque MFI
nao tem valores depois
vs(i)= MFI(i)*0.35 + RSI(i)*0.65;

    if upper(i) < Excel.Close(i) %sell signal
        vs(i)= vs(i)+15;
    end
end

end
```

```

if lower(i) > Excel.Close(i) %buy signal
    vs(i)= vs(i)-15;
end

```

### **To construct the “dte” indicator:**

%FIRST: PREDICT A BIG MOVE:

```

%I want a value of historical volatility indicator low and that is growing fast
function dte=trade(HISTVOL,N) %N é o usado no histvol
daystoenter=[] %list to be added the days to enter
for i= N+1:length(HISTVOL)-1 % ESTA MAL ESTA PARTE, MUDAR
    if HISTVOL(i)< mean(HISTVOL)*0.5 % talvez em vez de '50' meter aqui uma média ou assim
        if HISTVOL(i)-HISTVOL(i-1) > HISTVOL(i-1)-HISTVOL(i-2)> HISTVOL(i-2)-
HISTVOL(i-3)
            disp('ENTER POSITION, very low HISTVOL and growing')
            disp(i)
            daystoenter(end+1)= i;
        end
        if HISTVOL(i)-HISTVOL(i-1) < HISTVOL(i-1)-HISTVOL(i-2)
            disp('MIGHT BE SOON to enter position, very low HISTVOL, but still descending')
        end
    elseif HISTVOL(i)< mean(HISTVOL)*0.7 % talvez em vez de '50' meter aqui uma média ou
    assim
        if HISTVOL(i)-HISTVOL(i-1) > HISTVOL(i-1)-HISTVOL(i-2)> HISTVOL(i-2)-
HISTVOL(i-3)
            disp('ENTER POSITION, very low HISTVOL and growing')
            disp(i)
            daystoenter(end+1)= i;
        end
        if HISTVOL(i)-HISTVOL(i-1) < HISTVOL(i-1)-HISTVOL(i-2) %É MAU, indica que ainda
    está a decrescer
            disp('MIGHT BE SOON to enter position, very low HISTVOL, but still descending')
        end
    end
end

```

```

end
elseif HISTVOL(i) < mean(HISTVOL)*1
    if HISTVOL(i)-HISTVOL(i-1) > HISTVOL(i-1)-HISTVOL(i-2)
        disp('MIGHT BE SOON to enter position, very low HISTVOL and descending')
    end
    if HISTVOL(i)-HISTVOL(i-1) < HISTVOL(i-1)-HISTVOL(i-2)
        disp('NOT ENTER ANY POSITION YET,not ideally low HISTVOL and still descending, very
careful')
    end
end
elseif HISTVOL(i) >= mean(HISTVOL)*1
    disp('still early to look for volatility squeezes')
end
end
dte= daystoenter
end

```

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