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# Trading strategies for exchange traded funds: an application of technical analysis

Ana Lorena Jiménez-Preciado* Salvador Cruz-Aké**
Roberto Joaquín Santillán-Salgado***

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## Abstract

This paper aims to demonstrate the profitability of technical analysis indicators over buy and hold strategy with 3 of the most popular Exchange Traded Funds: SPY (SPDR S&P 500), DUST (Direxion Daily Gold Miners Index Bear 2x Shares) and EDZ (Emerging Markets Direxion Daily MSCI Emerging Markets Bear 3X Shares). A Binary Trading System is proposed to make algorithmic trading in a low-frequency environment, including Bollinger Bands and Williams' Percent Range technical analysis indicators, whose results are compared to a Buy & Hold strategy as a benchmark. The main contribution of this work is to present evidence that the Binary Trading System allows profiting even in downtrend scenarios, even after including the broker's commission. The Binary Trading System, validated through trading performance metrics, gives accurate buy and sell signals improving over a Buy & Hold strategy, and reduces potential equity losses.

*Palabras clave*: algorithmic trading, low-frequency, technical analysis, trading system, ETFs.
*Clasificación JEL*: G10, G12, G14.

* Profesora-investigadora en la Escuela Superior de Economía del Instituto Politécnico Nacional. <ajimenezp@ipn.mx>.
** Profesor-investigador en la Escuela Superior de Economía del Instituto Politécnico Nacional. <salvador.ake22@gmail.com>.
*** Profesor-investigador en la EGADE Business School del Tecnológico de Monterrey, México. <roberto.santillan@itesm.mx>.

# Estrategias comerciales para fondos cotizados en bolsa: una aplicación del análisis técnico


## Resumen

El objetivo de este estudio es demostrar la rentabilidad de los indicadores de análisis técnico sobre estrategias *buy & hold* tomando en cuenta 3 de los Exchange Traded Funds más populares: *SPY* (*SPDR S&P* 500), DUST (*Direxion Daily Gold Miners Index Bear 2x Shares*) y EDZ (*Emerging Markets Direxion Daily MSCI Emerging Markets Bear 3X Shares*). El sistema propuesto se enfoca al trading de baja frecuencia incluyendo las herramientas de Bandas de Bollinger y el Rango de Porcentaje de Williams, cuyos resultados son comparados con la estrategia de *Buy & Hold* que se toma como punto de comparación. La principal contribución de este trabajo es que el Sistema Binario de Trading creado permite obtener rendimientos positivos incluso en momentos de tendencia a la baja y volatilidad, aún después de incluir las comisiones de los intermediarios bursátiles. El Sistema Binario de Trading se valida a partir de métricas de desempeño, proporciona señales precisas de compra y venta y reduce perdidas potenciales de capital.


*Keywords*: trading algorítmico, baja frecuencia, análisis técnico, sistemas de trading, ETFs.
*JEL classification*: G10, G12, G14.

## 1. Introduction

The analysis of the financial markets and the diversity of instruments currently listed on different countries' stock exchanges has led to the development of tools that range from the most traditional (such as technical and fundamental analysis) to valuations that implement sophisticated models, based on their computational power and mathematical sophistication, combined with an outlook stand supported with macroeconomic information and political news. Nowadays, buy and sell of securities are done in milliseconds -low latency trading- in frequencies or timeframes less than a day (minutes, hours) -intraday trading- investment positions that take days (swing trading) and buy & hold strategies that are frequently used in the composition of investment portfolios.

There is an intense debate on which are the best tools to analyze the market, especially in times of uncertainty when it seems that the stock markets are collapsing. A "sweet spot", so to speak, is that there are funds that yield positive returns even when bear markets occur. These funds give investors and traders the possibility to win even when stock prices fall. Alternatively, there are funds that serve like a hedge asset (mainly gold and silver) during financial turmoil. The funds that replicate an underlying asset or a basket of shares are known as Exchange Traded Fund (ETF) and can be used to trade indices, commodities, currencies, bonds, energy, and even specific sectors or a mix of different instruments. Thanks to their design and the leverage they use, ETF profit even during bear markets and offer extraordinary returns over a winning streak of the market.

The main goal of the present work is to present a trading system based on technical analysis in which a binary signal system is generated from two indicators: Bollinger Bands and Williams' Percent Range (trend-following and mean-reversion strategies). The outcome of implementing the system, including the broker's commission (considered to be a 0.25% fee as the average commission for buy and sell positions in Mexico), shows that the annualized return obtained is superior when compared against a buy and hold strategy.

Three ETFs are used: SPY (SPDR S&P 500), DUST (Direxion Daily Gold Miners Index Bear 2x Shares) and EDZ (Emerging Markets Direxion Daily MSCI Emerging Markets Bear 3X Shares); SPY represents the S&P500, one of the main indexes in the stock market; the second, replicates the behavior of gold and silver, and is considered a safe asset against volatility and downtrends in the stock market (although this ETF's profit is two times the inverse of uptrend prices); and, finally, EDZ that pays three times the inverse of assets listed in emerging economies.

The most important contribution is the presentation of the results of implementing a low-frequency binary trading system based strategy that compares the performance of any financial instrument (as long as open, maximum, minimum and closing prices are provided), applying technical analysis strategies (either Bollinger's or Williams's) with respect to a buy & hold strategy. The comparison is based on the annualized performance, including broker commissions, of the alternatives. The low-frequency binary trading system is tested from january 2018 to march 2020 to attain a more thorough analysis. The main finding of the analysis is that Williams %R is the best strategy for inverse ETFs.

The second part of this paper introduces the link between the EMH and trading strategies, including a brief literature review on this subject. The third par focuses on Trend-Following and Mean-Reversion strategies. The fourth part compares the performance of the technical indicators-based investment strategy with the conventional buy and hold strategy. Finally, the fifth part presents the conclusions of this exercise and suggest some future lines of research.

## 2. From efficient markets to trading strategies
### *2.1 Random walks and efficient market hypothesis*

Since the publication of the seminal paper on the Efficient Market Hypothesis (EMH) (Fama, 1970) and the acceptance of the underlying principle that a market[1] is efficient in the sense that the price of any security always "fully reflects" all available information, eliminating the possibility of taking advantage of spreads and limiting predictability of the same prices -insomuch as they behave as a random walk process-, the EMH continues to be the basis of modern financial studies, despite its limitations (Jovanovic, 2018) and (Ball, 2009).

Fama (1965, 1970), assume assumed that a random walk process represents stock prices, and since new information arises, stock prices incorporate the latest information. When we assume a weak efficient market, then a Martingale model explains the way in which information is incorporated to the market prices, this is:

$$E(\tilde{r}_{j,t+1}|\Phi_t) = 0 \tag{1}$$

where $E$ refers to the expected value operator, $\tilde{r}_{j,t+1}$ is the return of a financial asset, and $\Phi_t$ is the set of information known at time t. Altogether $E(\tilde{r}_{j,t+1}|\Phi_t)$ reflects the expected return (equilibrium) conditioned by a sigma - field $\Phi_t$. The expectations of future value are equal to the present value based on the information provided by the parameter $\Phi_t$. If the expected future value is greater than or equal to the present value, then a sub-martingale is formed. In the case of an investor using a "buy & hold" strategy, betting for a long run positive return, we may say that the investor is expecting a submartingale, this is:

$$E(\tilde{r}_{j,t+1}|\Phi_t) \geq 0 \tag{2}$$

The sub-martingale in equation 2 implies that conditionals returns on $\Phi_t$ cannot be negative. Collectively, the statement that prices fully reflect all available information and that this is as a stochastic process leads to a model where prices behave as a random walk.

$$f(r_{j,t+1}|\Phi_t) = f(r_{j,t+1}) \tag{3}$$

As new information randomly arrives, stock prices will fluctuate randomly as well. According to (Fama, 1970), the market's efficiency sufficient conditions

[1] Whether a physical or virtual space, a market is defined as the place where operations of securities trading are made.

are: 1) no transaction costs exist for trading, 2) all market agents have access to all available information at no cost, and 3) when new information arrives, all markets participants process it in the same way and optimize their investment decisions.

Notwithstanding, the assumptions of the EHM are restrictive and improbable. For that reason, this paper assumes a framework of semi-strong efficiency[2] in the sense that the set of information $\Phi_t$ includes historical prices and public information (e.g., annual reports, utilities, and even macroeconomics news) which are already reflected in securities' prices at any given time. In this regard, future stock prices' direction can be anticipated, and profits generated with strategies that benefit from the random walk process.

### 2.2. *Trading strategies literature*

Technical analysis focuses on analyzing securities prices by looking at their trend and momentum (trend persistency) over time. Likewise, technical analysis uses indicators and oscillators, which are calculated from formulas based on prices and volume (Troiano & Kriplani, 2011). Indicators and oscillators confirm buying and sell positions and partially predict the direction of the price of an asset. Even though the basis of trading with technical analysis is quite simple -buy at the lowest price and sell it at the highest- the challenge is when and how much to buy or sell (Escobar, Moreno, & Múnera, 2013). Several methodologies and indicators have been developed to that end. The most sophisticated models include Bayesian applications (Maragoudakis & Serpanos, 2016), machine learning that includes an artificial neural network, random forest, support vector machine and overall supervised, semi-supervised and unsupervised models (Jeet, 2017), financial econometrics (Stanković, Marković, & Stojanović, 2015), genetic algorithms (Kampouridis & Otero, 2017) and new indicators for technical analysis proposed by (Troiano & Kriplani, 2011) and (Berutich, López, Luna, & Quintana, 2016).

This document uses traditional technical analysis and postulates the hypothesis that technical indicators have a better performance measured by annualized returns and annualized volatility over a buy and hold strategy.[3] The profitability of these indicators can be seen in (Szakmary, Shen, & Sharma,

[2] In EMH, there are three types of efficiency: weak, semi-strong, and strong. The first one refers to a set of information that only includes history prices; semi-strong efficiency is, in addition to history prices, the readiness of public information. The strong way means the sum of semi-strong plus private information (such as monopolistic access to relevant information about prices).

[3] A buy and hold strategy is a long term investment (at least for one year) when an investor buys any kind of securities and holds them assuming that they will get a positive return, regardless of downtrends or stocks volatility.

2010) where the authors implemented crossover and threshold strategies with moving average and channel indicators for commodity futures; and in (Macchiarulo, 2018), who predicts the S&P 500 index with trading strategies and machine learning, specifically with trend indicators and threshold oscillators such as moving average, Parabolic SAR, Bollinger Bands, Relative Strength Index (RSI), Williams % R, stochastics and Ichimoku clouds.

Other applications of trading strategies with technical analysis can be found in (Rousis & Papathanasiou, 2018), who implement a survey in the Greek market to know the indicators that traders apply for buy/sell stocks. The main findings are that technicians prefer indicators and oscillators over patterns analysis and a time-table of one day rather than intraday trading. In (Hadj-Ayed, Loeper, & Abergel, 2019) a moving average-based strategy is compared with an optimal portfolio, to find that the first has a better performance; both strategies were tested with logarithmic returns as a function of the model parameters.

Trading strategies, either mixed with statistical methods, econometrics, machine learning, or the use of indicators by themselves, provide information about trend prediction and the possibility of choosing strategies based on their performance. The next section describes the steps to set up the trading strategy proposed, as well as the indicators/oscillators that are implemented.

## 3. Trend-following and mean-reversion strategies

### *3.1 Lagging and leading indicators*

A classification of technical analysis strategies is based on either lagging or leading indicators/oscillators; the first refer to price trend-following and the second focus on trend-momentum or mean-reversion. Both lagging, and leading indicators identify conditions to buy and sell, i.e., trading signals. Trading signals try to identify uptrend, downtrends, and momentum, which is the tendency of raising or falling prices to maintain their inertia.

Depending on the indicator or oscillator applied, these tools take information from open, close, high, and low pricing formation of the securities. While there are plenty of technical indicators, only those that are implemented in this study will be described, in particular, the Bollinger Bands for trend-following and Williams' %R mean reversion indicator.

### *3.2. Bollinger Bands*

John Bollinger created Bollinger Bands in 1992. Despite the development of new tools for technical analysis, it stands today as one of the most popular strategies (Bollinger, 2002). The particularity of this indicator is that it is based on the volatility of the n days Simple Moving Average (SMA):

$$SMA_n = \frac{\sum_n Close}{n} \tag{4}$$

where *n* refers to the number of observations considered from a given period. The selection of the days for the construction of the *SMA* helps to capture different trend frames; as the SMA period of observation increases, the smoother the series becomes. On this basis, Bollinger Bands are defined as the standard deviation or volatility ($\sigma$) over the $SMA_{20}$. This is considered to be a tool to identify overbought and oversold areas.

$$\begin{aligned} &\text{Middle Band} = SMA_{20} \\ &\text{Upper Band} = SMA_{20}+2\sigma_{20} \\ &\text{Lower Band} = SMA_{20}-2\sigma_{20} \end{aligned} \tag{5}$$

As $\sigma$ increases, Bollinger Bands will get wider and confirm the trend of the asset's price. If the closing price touches the upper band, then it is said to be overbought; when the closing price crosses the lower band, it is considered an oversold stock. Bollinger Bands are part of trend-following tools since their construction is based on SMA.

### *3.3. Williams percent range (%R)*

Williams %R, also known as the Williams Percent Range, is a momentum oscillator that highlights overbought and oversold areas. Williams %*R* is used for establishing entry and exit positions. This indicator compares the closing price with a high and low-price range. Williams %*R* is distinguished by its measurement of the strength or weakness of a stock's trend (Wilder Jr, 1978). Williams %*R* is also a bounded oscillator which divides the difference between the Highest High (HH) price of the last 14 days and the day's closing price, and divides it by the range between the Highest High and the Lowest Low (LL) price of the last 14 days, as follows:

$$W_{14} = \frac{HH_{14} - Close}{HH_{14} - LL_{14}} \tag{6}$$

where $W_{14}$ is the 14 days Williams Percent Range. Williams %*R* ranges from 0 to 1. When the indicator fluctuates between 0 and 0.2, it indicates an oversold condition. When the readings are from 0.8 to 1, it is interpreted as an oversold condition. Williams %*R* is considered a mean-reversion tool because of its boundaries and its fluctuation within thresholds.

### *3.4. Application of Bollinger Bands and Williams %R over ETFs*

Exchange-Traded Funds or ETFs are financial assets traded like a stock. ETFs began their development in the American Stock Exchange in 1989. Their distinctive feature lies in their flexibility to replicate underlying assets that are not easy to acquire for an investor like indexes, commodities, bonds, currencies, and even mutual, hedge, and leveraged funds (Gastineau, 2001). For example, if a stock index (like S&P500) is rising, unless the investor or trader participates in a derivatives market, for an everyday investor it is not possible to take advantage of the uptrend index. This is when ETFs become special since they track the S&P500 behavior turning them into a liquid asset listed as a stock exchange.

ETFs can be classified according to their capitalization or financial-industry sector. In this regard, this paper works whit three different types of ETFs that are among the most popular ETFs traded in the United States, according to Yahoo Finance and Investing: the SPY, which replicates a market-cap-weighted and midcap portfolio of stocks included in the S&P 500. index. The second ETF is DUST that tracks a market-cap-weighted index of global gold and silver-mining; this ETF provides 2x the inverse exposure of the mining firms[4] And finally, EDZ replicates the MSCI Emerging Markets[5] and it's a 3x leverage bear ETF.

The idea of selecting different types of sectors (index for SPY, a commodity for DUST, and emerging markets for EDZ) is to demonstrate that the technical analysis strategies proposed, the Bollinger Bands and Williams %R, have an advantage over a buy and hold strategy. Figure 1 represents the behavior of the closing price of SPY, including the technical analysis indicators. From January 2018 to January 2020, the ETF presented an upward trend. From there, the S&P 500 posted a decline due to the intensification of trade tensions, particularly those between the US and China (Carvalho, Azevedo, & Massuquetti, 2019). Afterward, the spread of the COVID-19 pandemic[6] coupled with the sharp decline of oil prices due to the conflict between Saudi Arabia and the Organization of Petroleum Exporting Countries (OPEC) is reflected in a profound drop in SPY, falling to close to $200.

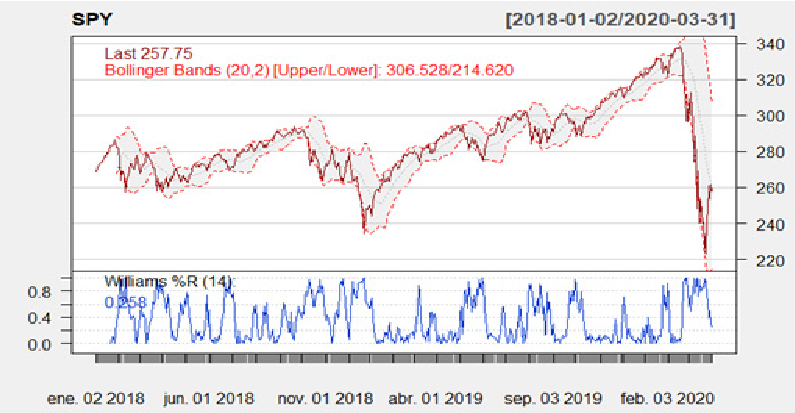
The reading of technical indicators is described as follows. In essence, every time that the closing price touches the upper band then is said that the ETF is overbought and the price will bounce down; the same effect can be

[4] The mining country weightings are mostly Canada, the US, Australia, and South Africa.

[5] MSCI Emerging Markets Index stands for Morgan Stanley Capital International (MSCI).

[6] The impact of the coronavirus sparked off substantial declines in the Asian, European and American stock markets greater than 5% in a single day leading to the cancellation of market transactions for a few hours.

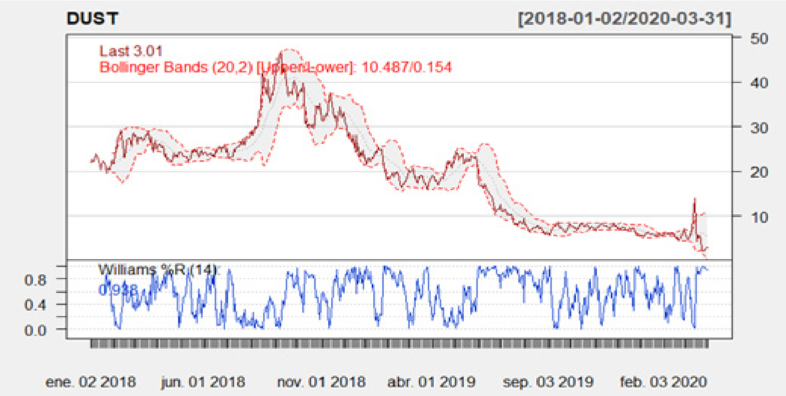
observed when the price falls into the lower band, in this scenario, the asset is in an oversold area and bounces up. The wider the bands, the more presence of volatility in the ETF is. In the case of William %*R*, when the line is above 0.8, then the ETF is overbought, and when the indicator crosses from above the threshold of 0.8, then the closing price drops, and it's time to sell the asset. Now, if Williams %*R* is below 0.2, then it is in the oversold area, and the buy signal occurs when the indicator outstrips the 0.2 threshold.




Source: own elaboration in *R* programming language based on (Jeffrey & Ulrich, 2019).

Figure 1
SPY closing price performance from 2018-01-02 to 2019-03-31

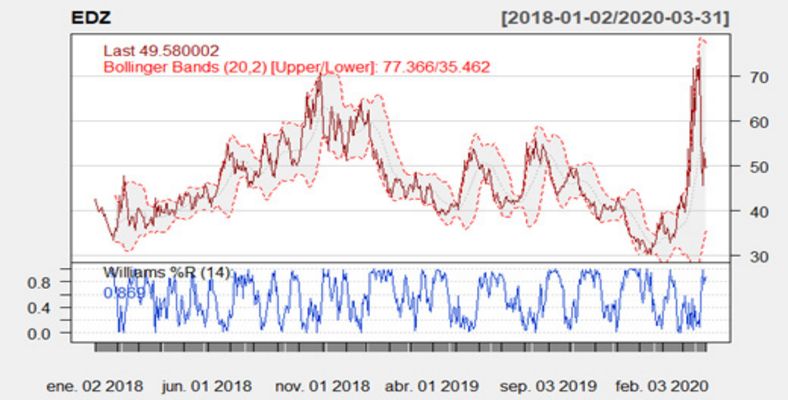
Figure 2 denotes the performance of DUST, from January 2018 to september 2020. The closing price fluctuated between 20dlls and 48dlls exhibiting an uptrend. However, it was not until october 20 when gold and silver prices started to rise, pulling down the price of the ETF. It is noteworthy that since DUST has an inverse correlation with SPY, a fly to quality would be expected when the prices of gold and silver decline due to optimism in the stock market, however, the ETF falls below $10dlls, showing the recovery of metals' prices. In mid-March, when the impact of oil prices dropping due to the excess of oil production in the market during the COVID-19 quarantine, metal prices moved strongly downwards, leading DUST above 10dlls per title.




Source: own elaboration in *R* programming language based on (Jeffrey & Ulrich, 2019).

Figure 2
DUST closing price performance from 2018-01-02 to 2020-03-31

Furthermore, figure 3 shows the behavior of EDZ, an ETF that is integrated with emerging-market firms' stock (large and mid-cap). The ETF concentrates 31% of its investments in Chinese companies, more than 22% in Taiwan and South Korea firms and the other 50% is distributed among India, Brazil, South Africa, Russia, Thailand, Saudi Arabia, Mexico, Indonesia, and Malaysia. Emerging economies exhibit a downtrend from January 2018 to October 2018, pushing EDZ to reach its 70dlls resistance. The global recovery of the stock indices that followed produced a steep drop for EDZ. Nevertheless, in more recent times, the volatility caused by the spread of COVID-19 pandemic and tensions over oil triggered EDZ titles over $70dlls in less than a month.




Source: Own elaboration in R programming language based on (Jeffrey & Ulrich, 2019).

Figure 3
EDZ closing price performance from 2018-01-02 to 2019-10-30

## 4. Technical indicators performance vs. buy & hold strategy

According to (Lee & Seo, 2017) there are three types of frequencies of trading: 1) low-frequency trading which refers to trading positions measured by days or weeks, 2) high-frequency trading or intraday trading (buy and sell positions over minutes and hours timeframes) and 3) ultra-high frequency which are transactions done in seconds or millisecond.

The basis of the algorithm for this study focuses on the use of a low-frequency model despite the growing popularity of high and ultra-high frequency trading. This is because the strategy is based on statistical models and technical analysis instead of connection speed or sophisticated software/hardware availability. Single indicators signals (Bollinger Bands and Williams %R) are implemented to follow bull (upwards) and bear (downwards) trend by identifying oversold/overbought areas for ETF's. Trading strategies based on technical indicators are described below:

Table 1
Buy and sell signals with bollinger Bands and Williams %*R*

| Kinf of Strategy | Buy Signal | Sell Signal |
|---|---|---|
| Trend-following with Bollinger Bands | $Day_n$: Close > Lower Band<br><br>$Day_{n+1}$: Close < Lower Band | $Day_n$: Close < Upper Band<br><br>$Day_{n+1}$: Close > Upper Band |
| **Kinf of Strategy** | **Buy SignalI** | **Sell Signal** |
| Mean- reversion with Williams %R | $Day_n$: $W_{14}$> 0.80 Upper Threshold<br><br>$Day_{n+1}$: $W_{14}$< 0.80 Upper Threshold | $Day_n$ : $W_{14}$>0.20 Lower Threshold<br><br>$Day_{n+1}$ : $W_{14}$<0.20 Lower Threshold |

Source: own elaboration.

According to the strategies showed in Table 1, for the trend following strategy with Bollinger Bands, if the closing price is higher than the lower band and the next day, the closing price is below the lower band, then, a buy signal is confirmed, i.e, the ETF is oversold. If the closing price is lower than the upper band and the next day the closing prices break the upper band, then, a sell signal is corroborated, i.e., the ETF is overbought. Similarly, with the mean reversion strategy using Williams %R, if $W_{14}$ is above the 0.80 upper threshold and the next day the $W_{14}$ crosses under the 0.80 bound, a buy signal is produced. The asset is oversold, when $W_{14}$ is above the 0.20 lower threshold, and in the $Day_{n+1}$ breaks the 0.20 threshold, then a sell signal is confirmed, i.e., the ETF is oversold.

Buy and sell signals from both strategies (Bollinger Bands and Williams %R) are classified as follows (table 2):

Table 2
Buy and sell signals classification

| Signal | Class signal |
|---|---|
| Buy signal | 1 |
| Sell signal | -1 |
| Hold signal | 0 |

Source: own elaboration.

Every time that a buy signal is confirmed, it is assigned a classification "1"; if a sell signal is identified, then the classification is "-1", and if there is no signal, then a hold position is assumed with "0". If we have a buy signal, another "1" is assigned stating that we own the ETF, and this is held until a sell position is confirmed, then is assigned a "0," indicating that we no longer own the ETF.[7] The results are shown in table 3.

Table 3
Buy and sell positions

| Position | When buy/sell signal confirmed |
|---|---|
| Own the ETF | 1 |
| Don't own the ETF | 0 |

Source: own elaboration.

Finally, the strategy is implemented evaluating a buy a hold position, every single technical indicator, and the same indicator with a 0.25% fee[8] Plus, 16% of Value Added Tax (VAT) for every buy and sell signal confirmed. We use performance metrics to evaluate strategies risk-adjusted returns. Main performance metrics include the annualized return and annualized standard deviation. Annualized return corresponds to the yearly cumulative product of daily trading ETF returns.

$$r_a = \left[\prod_{t=1}^{n}(r_t + 1)\right] - 1 \tag{7}$$

[7] Appendix 1 shows an example of the result of EDZ.
[8] based on the average commissions charged by brokers in México.

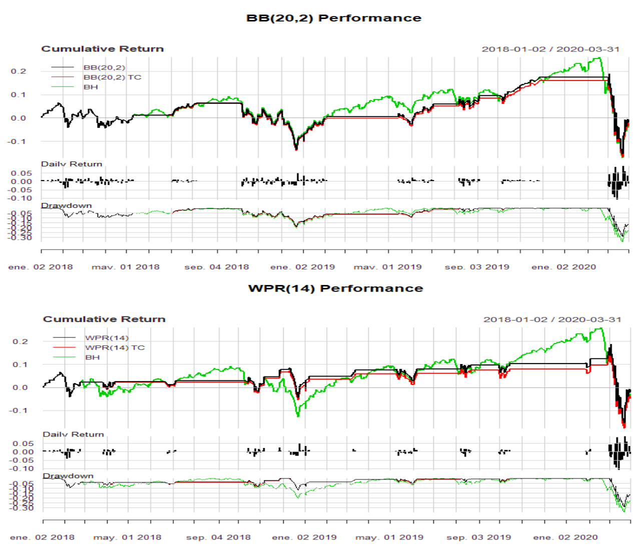
Where $r_a$ is the annualized return, and $r_t$ is the daily return of ETFs. Moreover, the annualized standard deviation is used and corresponds to converting daily returns variability to a yearly frequency:

$$\sigma_a = \sigma * \sqrt{252}$$

$$\sigma = \sqrt{\frac{1}{n} * \sum_{t=1}^{n} (r_t - \mu)^2} \tag{8}$$

$$\mu = \frac{\sum_{t=1}^{n} r_t}{n}$$

where $\sigma_a$ is the annualized standard deviation, and $\sigma$ is the daily standard deviation, and $\mu$ is the average daily returns. In order to have an appropriate sample[9] that allows the comparison of the strategy; the temporality is considered from January 2018 to March 2020 with daily data. The purpose of incorporating the first quarter of 2020 is to capture the abrupt price movements observed in financial markets due to the COVID-19 pandemic and the drop in oil prices. Figure 4 shows the results of strategies for SPY.




Source: own elaboration in *R* programming language based on (Peterson & Carl, 2019).

Figure 4

SPY strategies performance as of cumulative return 2018-01-02 / 2020-03-31

[9] For trading strategies testing and validation (usually through backtesting), at least one year of the sample is commonly used (Jiarui & Zhang, 2005).

Figure 4 shows the cumulative return of SPY with the strategies performance of buy & hold, Bollinger Bands (with and without commission), and Williams %R also with and without commission. The line in green represents the behavior of the closing price as is, while the black and red line shows the application of the trading strategy with the binary system every time the buy signal is given, it is assumed that the SPY is bought. The accumulated yield for each trade is added once the buy position is made (and is not necessarily a positive return since the signal is given from the crosses-over of prices and signals rules).

The purpose of comparing it against a strategy that includes a commission is that the result is more attached to what a trader or investor can get once the cost of commissions is absorbed. Likewise, figure 4 presents the drawdown that shows the distance to the highest performance or peaks (which can change as new peaks form) as well as the daily returns of the strategy. This can be seen in table 4.

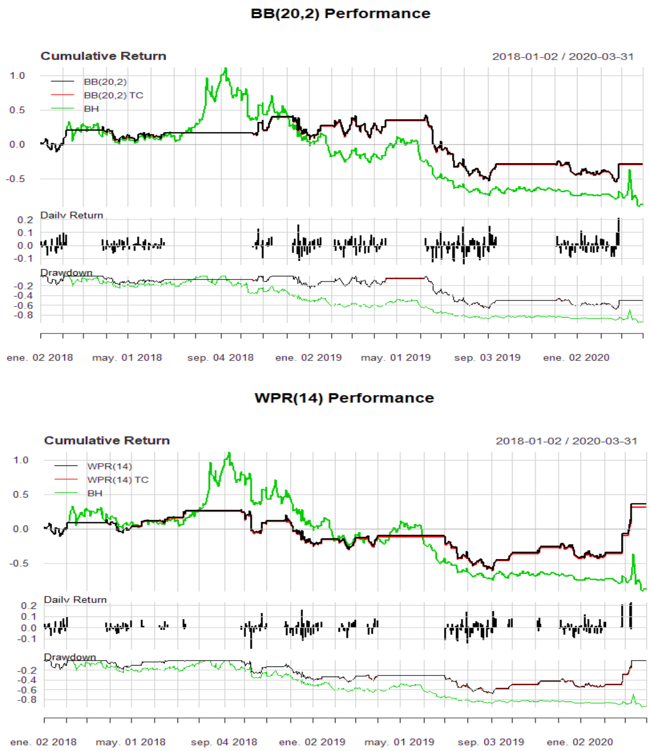
Table 4
Performance metrics for SPY from january 2018 to march 2020

| **Performance Metrics** | **Buy&Hold** | **Bollinger** | **Bollinger with fee** | $W_{14}$ **%$R$** | $W_{14}$ **%$R$ with fee** |
|---|---|---|---|---|---|
| Annualized return | -1.85% | -0.93% | -1.59% | -0.99 % | -2.19% |
| Annualized standard deviation | 23.05% | 21.44% | 21.45% | 20.51% | 23.05% |

Source: own elaboration.

Performance metrics are based on annualized return and annualized standard deviation to verify the effectiveness of the strategies. In the case of SPY, the ETF that tracks the S&P500 has had an annualized cumulative return from January 2018 to March 2020 of -1.85% and an annualized volatility of 23.05%, if the binary trading system had chosen a strategy with Bollinger Bands would have decreased to -0.93% and with a commission of -1.59%. On the other hand, Williams% *R* with the commission is worse, compared to buy & hold and Bollinger: both technical strategies have slightly lower risk volatility than buy & hold. This result suggests that Bollinger Bands improve slightly (in this case, they reduce losses) compared to buy & hold while Williams% *R* does not represent the best solution for SPY.

As for DUST, which profits 2x the inverse of the MISC index of gold and silver mining companies, outcomes exhibit that both strategies Bollinger and Williams remain mostly above the closing price, which indicates better performance in terms of the yield generated. Table 5 shows the performance metrics associated with DUST, which present a cumulative annualized negative return of -58.80% and a higher risk exposure (more than 100% volatility).




Source: own elaboration in *R* programming language based on (Peterson & Carl, 2019).

Figure 5
DUST strategies performance as of cumulative return 2018-01-02 / 2019-10-30

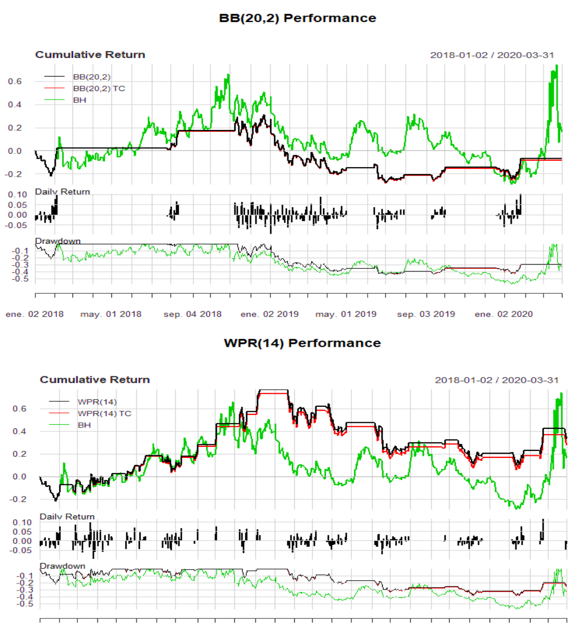
It is noteworthy that Bollinger Bands, including their construction, is based on volatility, it is not the best strategy since it reduces losses to -13.81% and -14.37% respectively, while Williams allows to profit 12.98% of annualized return and decreases the annualized deviation to 60.27%. This is shown in table 5.

Table 5
Performance metrics for DUST from january 2018 to march 2020

| **Performance Metrics** | **Buy&Hold** | **Bollinger** | **Bollinger with fee** | $W_{14}$ **%*R*** | $W_{14}$ **%*R* with fee** |
|---|---|---|---|---|---|
| Annualized return | -58.80% | -13.81% | -14.37% | 14.73% | 12.98% |
| Annualized standard deviation | 109.20% | 59.26% | 59.25% | 60.32% | 60.27% |

Source: own elaboration.

Finally, EDZ displays similar results to DUST, since the best strategy for this ETF is to apply Williams %*R*. The buy & hold strategy performance is, in most cases, above the Bollinger strategy, while in the case of the Williams strategy, the opposite happens; this can be seen in figure 6. Regarding the performance metrics that are presented in table 6, the annualized return for EDZ was 6.95%, while volatility was 73.85%.




Source: own elaboration in *R* programming language based on (Peterson & Carl, 2019).

Figure 6
EDZ Strategies performance as of cumulative return 2018-01-02 / 2020-03-31

Although Bollinger Bands reduce the annualized standard deviation, this strategy generates a negative return (around 3%). In comparison, the yield generated by Williams beats the buy & hold strategy by 13.60% and 11.56%, including the trading fee.

Table 6
Performance metrics for EDZ from january 2018 to march 2020

| Performance Metrics | Buy&Hold | Bollinger | Bollinger with fee | $W_{14}$ %$R$ | $W_{14}$ %$R$ with fee |
|---|---|---|---|---|---|
| Annualized Return | 6.95% | -3.18% | -3.72% | 13.60% | 11.56% |
| Annualized Standard Deviation | 73.85% | 31.48% | 31.47% | 31.67% | 31.73% |

Source: own elaboration.

## 5. Conclusion and future works

The main objective of this paper was to demonstrate the profitability of Bollinger Bands and Williams %$R$ using a low-frequency binary Trading System. We used 3 ETFs: SPY (which tracks S&P 500), and 2 inverse ETF: DUST (replicates a basket of gold and silver mining) and EDZ (which tracks Emerging Markets Bear 3X Shares). The idea of using ETFs is to represent different economic sectors' stock market performance (indices, metals, and emerging economies for this paper) but, most of all, show how these indicators work even in times of downward trends and volatility.

Daily data was downloaded to feed the Trading System from january 2018 to march 2020. Two years are incorporated to give enough training time to the binary system, and the first quarter of 2020 is incorporated due to the high volatility registered due to the spread of the COVID-19 pandemic and the drop in oil prices. While there are hundreds of technical analysis tools, a trend following strategy (Bollinger Bands) and a mean reversion strategy (Williams %$R$) are used because of their popularity and ease of implementation; however, the System allows to include and compare more strategies of technical analysis, a topic that can certainly be expanded for research.

Performance metrics are compared to rule the best strategy: annualized return and standard deviation in such a way that the best strategy for each ETF is identified, as well as the risk associated with it. Besides, a 0.25% commission is included, which is the average commission charged by brokers (in the case of Mexico) in order to obtain a real return on traders' payments.

Significant outcomes of this work highlight that in the case of the SPY, both Bollinger and Williams %*R* do not seem to produce outstanding returns, in comparison to a buy & hold strategy, despite their persistent uptrend before the fall observed during the first quarter of 2020. However, in the case of reverse ETFs such as DUST and EDZ, Williams %*R* makes it possible to capture positive returns even when the annualized return of the ETF is negative (like DUST) and to capture a positive return beyond the annualized return of EDZ. In both ETFs, Williams also significantly reduces the associated risk, although Bollinger is based on volatility, and would be a better proposal, in both cases, it fails.

The main contribution of this work is the proposal of a binary trading system that allows comparing different instruments (in addition to ETFs, it applies to any asset as long as it has OHLC prices) through the utilization of technical analysis strategies (for this work two of the most popular are compared: Bollinger and Williams %*R*). Performance metrics allow us to compare annualized return and the risk associated with them, in that sense, it is possible to choose the best strategy when investing as well as the possibility of hedge of negative returns. Although the discussion on which instruments and which strategies are the best is open, the goal remains unchanged: to profit, and we believe that any system that allows it, provide more significant elements to investors and traders for decision-making. We do not have a crystal ball, but we are in a constant search to improve the prediction and valuation proposals, and this is undoubtedly an incentive to continue expanding this line of research.

## Appendix 1

### Example of buy/sell signals implementation and positions from 2018-12-18 to 2019-01-18

| EDZ | Close | Lower Band | Upper Band | Signal | Position |
|---|---|---|---|---|---|
| 2020-01-15 | 31.6300 | 30.7286 | 35.5684 | 1 | 1 |
| 2020-01-16 | 31.0000 | 30.5312 | 35.3668 | 0 | 1 |
| 2020-01-17 | 30.5300 | 30.2513 | 35.2577 | 0 | 1 |
| 2020-01-21 | 32.8100 | 30.2925 | 35.0285 | 0 | 1 |
| 2020-01-22 | 32.0900 | 30.2821 | 34.8176 | 0 | 1 |
| 2020-01-23 | 33.0200 | 30.3260 | 34.6910 | 0 | 1 |
| 2020-01-24 | 33.8400 | 30.3779 | 34.5797 | 0 | 1 |
| 2020-01-27 | 37.2900 | 29.6883 | 35.6517 | 0 | 1 |
| 2020-01-28 | 36.3100 | 29.4020 | 36.2950 | -1 | 0 |
| 2020-01-29 | 35.9200 | 29.2855 | 36.6468 | 0 | 0 |
| 2020-01-30 | 37.4800 | 28.9231 | 37.4309 | 0 | 0 |
| 2020-01-31 | 39.7000 | 28.4980 | 38.6464 | -1 | 0 |
| 2020-02-03 | 38.5300 | 28.3228 | 39.3875 | 0 | 0 |
| 2020-02-04 | 35.4000 | 28.3714 | 39.4996 | 0 | 0 |
| 2020-02-05 | 34.8200 | 28.4135 | 39.5441 | 0 | 0 |
| 2020-02-06 | 34.7800 | 28.4957 | 39.6026 | 0 | 0 |
| 2020-02-07 | 36.2900 | 28.6751 | 39.8119 | 0 | 0 |
| 2020-02-10 | 35.6200 | 28.9586 | 39.9320 | 0 | 0 |
| 2020-02-11 | 34.2300 | 29.4036 | 39.8307 | 0 | 0 |
| 2020-02-12 | 32.8300 | 29.7077 | 39.7247 | 0 | 0 |
| 2020-02-13 | 34.1200 | 30.0341 | 39.6436 | 0 | 0 |
| 2020-02-14 | 34.1700 | 30.4885 | 39.4901 | 0 | 0 |
| 2020-02-18 | 34.8200 | 31.1590 | 39.2347 | 0 | 0 |
| 2020-02-19 | 34.0800 | 31.3588 | 39.1719 | 0 | 0 |
| 2020-02-20 | 35.6900 | 31.8255 | 39.0502 | 0 | 0 |
| 2020-02-21 | 36.2300 | 32.1001 | 39.0613 | 0 | 0 |
| 2020-02-24 | 40.3900 | 31.9763 | 39.8547 | 0 | 0 |
| 2020-02-25 | 41.2200 | 31.7190 | 40.4016 | -1 | 0 |

*If we have a buy signal = 1, this means that we own the ETF if the signal is 0; this indicates that we hold the previous position. When the signal is -1 (sell signal), it is assumed that we don't have the ETF anymore (that's the reason why the position is 0), and this position will be change until we have a buy signal again.

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