E-ISSN 2389-8194

Vol. 10, No. 2
Julio-diciembre de 2023
doi: https://doi.org/10.16967/23898186.843

ARTÍCULOS ORIGINALES

Investment strategies based on investors' mood: Better for crypto

pp. 6-16

RAÚL GÓMEZ MARTÍNEZ*
MARÍA LUISA MEDRANO GARCÍA**
JAIME VEIGA MATEOS***

* Doctor in Business Economics and Finance. Universidad Rey Juan Carlos de Madrid, Madrid, Spain. E-mail: raul.gomez.martinez@urjc.es. ORCID: 0000-0003-3575-7970. Google Scholar: https://scholar.google.com.ec/citations?hl=es&user=yIo3nEgAAAAJ. Scopus Author ID: https://www.scopus.com/authid/detail.uri?authorId=55624260800.
** Doctor in Business Economics and Finance. Universidad Rey Juan Carlos de Madrid, Madrid, Spain. E-mail: marialuisa.medrano@urjc.es. ORCID: 0000-0003-1844-1034. Google Scholar: https://scholar.google.com/citations?hl=en&user=C4MEk7gAAAAJ. Scopus Author ID: https://www.scopus.com/authid/detail.uri?authorId=55342658600.
*** Chemical Engineer. Universidad de Santiago de Compostela, La Coruna, Spain: E-mail: jaime.veiga@rai.usc.es. ORCID: 0000-0002-7139-4743. Google Scholar: https://scholar.google.com/citations?hl=en&user=ZmLSU3UAAAAJ.

E-ISSN 2389-8194

Vol. 10, No. 2
Julio-diciembre de 2023
doi: https://doi.org/10.16967/23898186.843

COMO CITAR ESTE ARTÍCULO
How to cite this article:

Gómez, R., Medrano, M.L. and Veiga, J. (2023). Investment strategies based on investors' mood: Better for crypto. *Revista Perspectiva Empresarial*, *10*(2), 6-16.

Recibido: 27 de enero de 2023
Aceptado: 12 de julio de 2023

ABSTRACT **Objective.** Analyze the utility of an algorithmic trading system based on artificial intelligence models that uses Google Trends as predictor of dozens of financial terms, to predict the evolution of S&P 500 index and Bitcoin. **Methodology.** A trading algorithmic system has been developed that opens a weekly long or short position in S&P 500 and Bitcoin, following the signals issued by an artificial intelligence model that uses Google Tends as predictor for next week market trend. The artificial intelligence models were trained using weekly data from 2013 to 2018 and have been tested in a prospective way from February 2018 to December 2021. **Results.** Google Trends is a good predictor for global investors' mood. The artificial intelligence algorithmic trading systems tested in a prospective way has been profitable. Trading strategies based on investors' mood have been more accurate and profitable for Bitcoin (beating the evolution of the cryptocurrency) than for S&P 500 (not beating the index). **Conclusions.** This evidence opens a new field for the investigation of trading systems based on big data instead of Chartism. Although there are many trading systems based on Chartism, there are no artificial intelligence trading systems operating in real market, this investigation could be considered pioneer in this field.

KEY WORDS Big data, behavioral finance, investors' mood, artificial intelligence, Google Trends.

Estrategias de inversión basadas en el estado de ánimo de los inversores: mejor para las criptomonedas

RESUMEN **Objetivo.** Analizar la eficacia de un sistema de trading algorítmico basado en modelos de inteligencia artificial que utiliza Google Trends como predictor de términos financieros para pronosticar la evolución del índice S&P 500 y del Bitcoin. **Metodología.** Se ha desarrollado un sistema de trading algorítmico que abre una posición semanal larga o corta en el índice S&P 500 y en Bitcoin, siguiendo las señales emitidas por un modelo de inteligencia artificial que utiliza Google Trends como predictor de la tendencia del mercado de la semana siguiente. Los modelos de inteligencia artificial se entrenaron utilizando datos semanales desde 2013 hasta 2018 y se sometieron a pruebas prospectivas desde febrero de 2018 hasta diciembre de 2021. **Resultados.** Google Trends sirve como predictor fiable del estado de ánimo de los inversores globales. Los sistemas de trading algorítmico de inteligencia artificial que se sometieron a pruebas prospectivas demostraron ser rentables. Las estrategias de trading basadas en el estado de ánimo de los inversores proporcionan más precisión y rentabilidad para Bitcoin (superando la evolución de la criptomoneda) que para el S&P 500 (sin superar al índice). **Conclusiones.** Esta evidencia presenta un nuevo campo de investigación de sistemas de trading basados en *big data* y no en el chartismo. A pesar de la existencia de numerosos sistemas de trading basados en el chartismo, hoy no existen sistemas de trading de inteligencia artificial que estén operando en el mercado real. Por tanto, esta investigación se puede considerar pionera en este campo.

PALABRAS CLAVE *big data*, finanzas conductuales, estado de ánimo de los inversores, inteligencia artificial, Google Trends.

Estratégias de investimento baseadas no humor do investidor: melhor para criptomoedas

RESUMO **Objetivo.** Analise a eficácia de um sistema de negociação algorítmico baseado em modelos de inteligência artificial que utiliza o Google Trends como preditor de termos financeiros para prever a evolução do índice S&P 500 e do Bitcoin. **Metodologia.** Foi desenvolvido um sistema de negociação algorítmico que abre uma posição longa ou curta semanal no índice S&P 500 e em Bitcoin, seguindo os sinais emitidos por um modelo de inteligência artificial que utiliza o Google Trends como preditor da tendência do mercado para a semana seguinte. Os modelos de inteligência artificial foram treinados usando dados semanais de 2013 a 2018 e testados prospectivamente de fevereiro de 2018 a dezembro de 2021. **Resultados.** O Google Trends serve como um preditor confiável do humor dos investidores globais. Os sistemas de negociação algorítmica de inteligência artificial que foram submetidos a testes prospectivos provaram ser lucrativos. As estratégias de negociação baseadas no humor do investidor proporcionam mais precisão e lucratividade para o Bitcoin (superando a criptomoeda) do que para o S&P 500 (sem superando o índice). **Conclusões.** Esta evidência apresenta um novo campo de investigação sobre sistemas de negociação baseados em *big data* e não no chartismo. Apesar da existência de numerosos sistemas de negociação baseados no chartismo, hoje não existem sistemas de negociação de inteligência artificial que operem no mercado real. Portanto, esta pesquisa pode ser considerada pioneira neste campo.

PALAVRAS CHAVE *big data*, finanças comportamentais, humor do investidor, inteligência artificial, Google Trends.

Introduction

Algorithmic trading systems invest in financial markets in an unattended way, sending buy and sell orders to the market for a certain financial instrument, according to a complex mathematical algorithm. Most of the trading systems that are operating nowadays follows Chartism rules, but the irruption of big data in asset management has opened a new approach for algorithmic trading.

There are a number of studies that analyzes how investors' mood is affected by different factors, changes over time and may be conditioned by experience or training (Cohen and Kudryavtsev, 2012). These changes in investors' mood provide evidence of anomalies in the stock markets returns (Nofsinguer, 2005). Corredor, Ferrer and Santamaría (2013) claim that investor mood has a significant effect on stock performance.

Previous studies demonstrated that weather affect to the stock market returns (Hirshleifer and Shumway, 2003; Jacobsen and Marquering, 2008) as sunny climates are associated with an optimistic mood and then positive returns. On the other hand, seasonal patterns like vacations that implies the effect of "sell in May and go away" or the "Halloween" effect (Bouman and Jacobsen, 2002) means that securities market yield should be greater from November to April than from May to October. And strange as it may seem, the Moon (Yuan, Zheng and Zhu, 2006) implies different returns according to the different phases of the moon observing differences from 3 % to 5 % in yield from one phase to another.

Other studies are focused on how the sports results are another item that modifies investors' mood. Edmans, García and Norli (2007) studied the results of football, cricket, rugby and basketball; while others have focused on the NFL (Chang et al., 2012), football (Berument, Ceylan and Gozpinar, 2006; Kaplanski and Levy, 2010), and on cricket (Mishra and Smyth, 2010). Gómez and Prado (2014) performed a statistical analysis of the following stock markets session return after national team football matches. The results obtained show that after a defeat of the national team, we should expect negative and lower than average prices on the country's stock market, the opposite occurring in the case of a victory.

At this stage, if we believe that investor mood affects financial markets and their liquidity (Liu, 2015), the challenge is how could we quantify mood to predict market trend (Hilton, 2001). This objective leads us to a big data approach.

Searching online means a source of big data. Agarwal, Kumar and Goel (2019) review the research work about the impact of the information content of the Internet over the retail investors' trading patterns. Wu et al. (2013) use big data to predict market volatility, and Moat et al. (2013) use the frequency of use of Wikipedia to determine investor feelings. Apart from these stats, Google Trends is one of the sources researched. This service provides aggregated information on the volume of queries for different search terms and its evolution over time. So, academic literature evidence that Google Trends is a good predictor in Medicine (Carneiro and Mylonakis, 2009), Economy (Choi and Varian, 2012), Engineering (Rech, 2007), between others. In Finance, Moat et al. (2013) they point out that Google Trends is be able to anticipate the stock market falls because in the precede period investors reflects their concerns about financial market. In this way, Gómez (2013) elaborated a "Risk Aversion Index" based on the stats of Google Trends for certain economic and financial terms that relate to market growth. Through an econometric model, he shows that Google Trends provide relevant information on the growth of financial markets and may generate investment signs that can be used to predict the growth of major European stock markets. According to this approach, we propose an algorithmic trading system that issues buy and sell orders by measuring the level of aversion to risk, if an increase in tolerance towards risk implies a bull market and an increase in aversion to risk a bear market.

In this paper we will describe big data trading algorithmic systems that, instead of Chartism rules, use Artificial Intelligence —AI— models based on Google Trends to predict de evolution of two financial instruments, the S&P 500 index and Bitcoin.

After this introduction, it discusses the research methodology and what is the main hypothesis. I also know describes how the data was collected; presents itself the model outputs, followed with conclusions respective.

Methodology

The S&P 500 is an American stock market index based on the market capitalizations of 500 large companies having common stock listed on the NYSE, NASDAQ, or the Cboe BZX Exchange. The S&P 500 was developed and continues to be maintained by S&P Dow Jones company. The S&P 500 differs from the Dow Jones Industrial Average and the NASDAQ Composite index, because of its diverse constituency and weighting methodology. It is one of the most commonly followed equity indices, and one of the best representations of the US stock market.

On the other hand, Bitcoin is a decentralized digital currency created in January 2009. It follows the ideas set out in a white paper by the mysterious (under the pseudonym) Satoshi Nakamoto. Bitcoin offers the promise of lower transaction fees than traditional online payment mechanisms do, and unlike government-issued currencies, it is operated by a decentralized authority.

The following statistics are mainly used to measure the perform of an algorithmic trading system (Leshik and Crall, 2011): (i) *Profit/Loss*, the total amount generated by the system from its transactions over a certain period; (ii) *Success rate*, percentage of successful transactions out of the total transactions, if the percentage is above 50 %, the system is profitable and the higher the percentage, the better the system; (iii) *Profit Factor*, this rate shows the relationship between earnings and losses, by dividing total earnings by total losses. A rate higher than 1 implies positive returns and the higher the rate, the better; (iv) *Sharpe Ratio*, relates profitability to volatility, the higher the ratio, the better the performance of the system (Sharpe, 1994).

InvestMood Fintech developed in January 2017 several algorithmic trading systems for different financial instruments. According to Gómez (2013), the volume of searches registered in Google on financial terms has explanatory and predictive capacity on the evolution of the financial markets. Since 2004 in which Google Trends began to publish these statistics, it is observed that bearish markets imply high level of searches of terms such as crash, recession or short selling, while bull markets imply low levels of this searches. Bearing this in mind, InvestMood (a Spanish fintech company) has created big data algorithmic trading systems that open long or short positions following an AI model in which the predictors are Google Trends stats while the target variable is the next evolution of this index (up/down).

The process of the algorithm is the following one:

(i) Every Sunday an AI model is trained, using a weekly sample downloaded from Google Trends of dozens of economic-financial terms, and issue a prediction for next week trend. Google Trends consults have been limited to financial matters and do not have any restriction by localization.

(ii) The system opens a long or short position in the market following the prediction issued by the AI model and maintains a long or short open position until there is a new prediction in the opposite direction.

From this point, the hypothesis to study is the following one:

H1: A big data algorithmic trading system based on AI models over investors' mood can generate positive returns.

We will validate this hypothesis if we reach three evidences: (i) Net profit of the prospective simulation is positive; (ii) Success rate is higher than 50 %; (iii) Profit factor is higher than 1.

Data of S&P 500 and Bitcoin have been downloaded from Investing.com webpage. From this data we deduce our target variable that can only have two values: up/down. Goggle Trends has historic data available from 2004 in a monthly base and offers the last five years stats in a weekly base. We use data downloaded from Google Trends since 2013 to February 2018 to train our first AI model.

Each week, the sample increases with one more observation that we incorporate into the training dataset to generate a new AI model that we will use for the next prediction.

As this study have been done in a prospective way (we train the model every week, we generate the prediction, and we have to wait for a week to observe if the prediction is right or wrong) the study has been developed for almost 4 years.

Results

The AI models created for the trading systems has been trained using the algorithms of dVelox, a data mining tool developed by the IT firm Apara. These algorithms build a Bayesian Network (Bayes, 1763) like the Figure 1. For a better understanding Figure 2 shows the same model in 2D view.

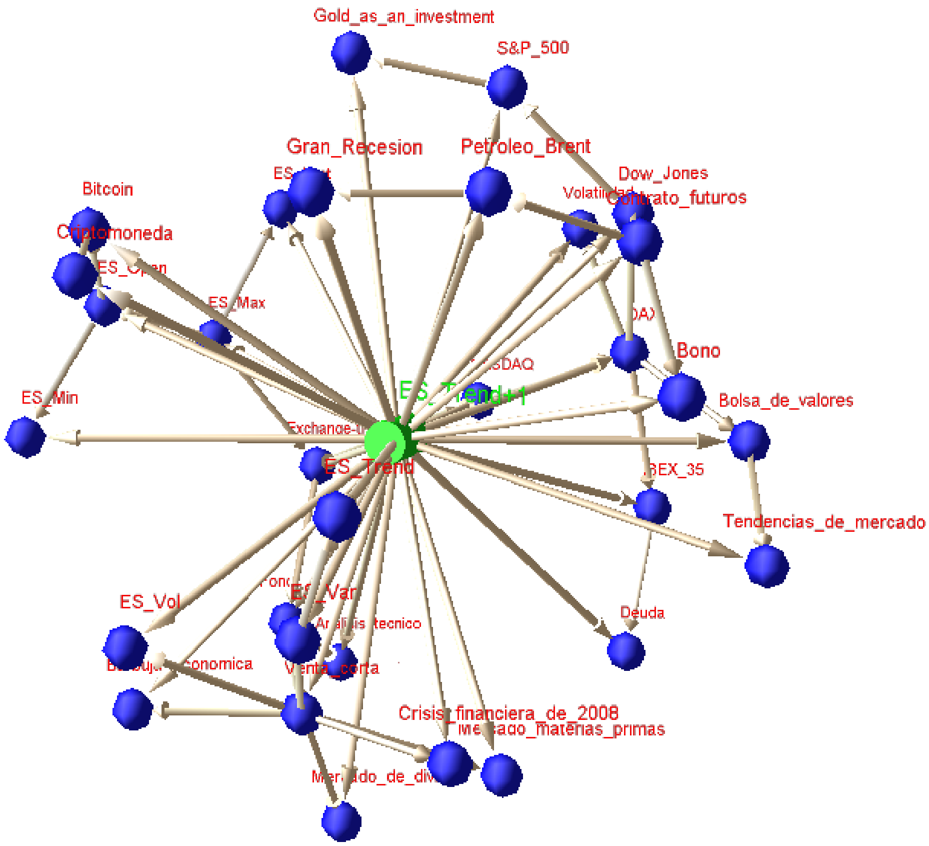

Figure 1. Bayesian Network for S&P 500 trading system. Source: authors own elaboration.

These graphs show the causality connection between our target variable (green, in this case the trend of S&P 500 next week, up or down) and the interest of the investors on different features of the market, measured by the number of searches made in Google, available in Google Trends. This is our explanatory variables as a metric for investors' mood.

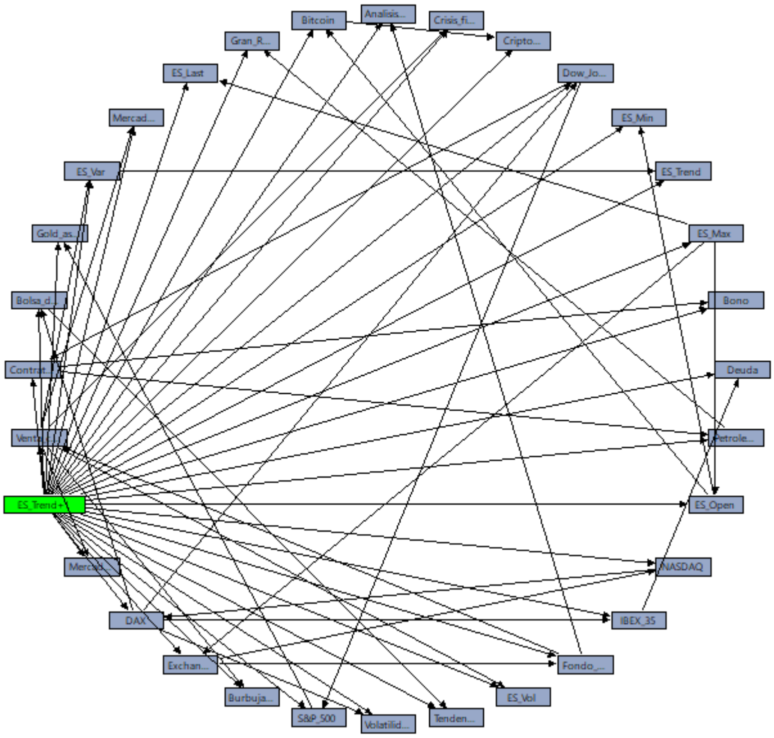

Figure 2. Bayesian Network for S&P 500 trading system (2D). Source: authors own elaboration.

In the same way, the model trained by dVelox for Bitcoin is shown in Figures 3 and 4.

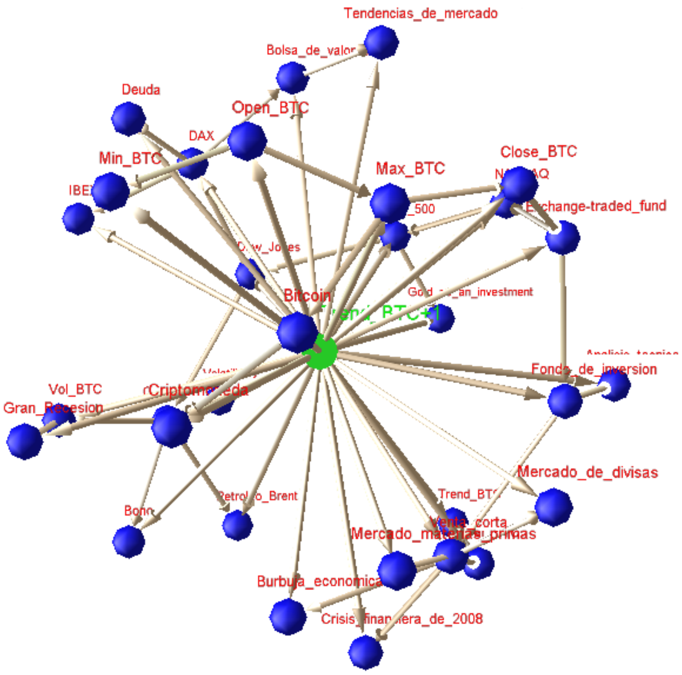

Figure 3. Bayesian Network for S&P 500 trading system (3D). Source: authors own elaboration.

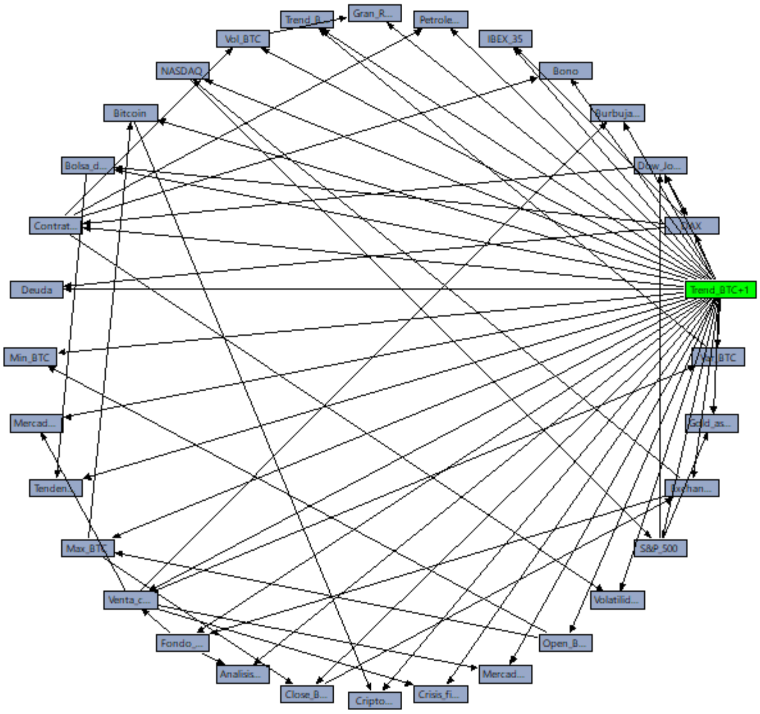

Figure 4. Bayesian Network for S&P 500 trading system (2D). Source: authors own elaboration.

Figure 5 sums up the performance of the S&P 500 system, form February 2018 to December 2021. The figure shows the evolution of the total return of the trading system that opens a weekly long or short position following the signal of the AI model shown in figures 1 and 2. On the other hand, it also show the evolution of the S&P 500, that could be like a indexed fund.

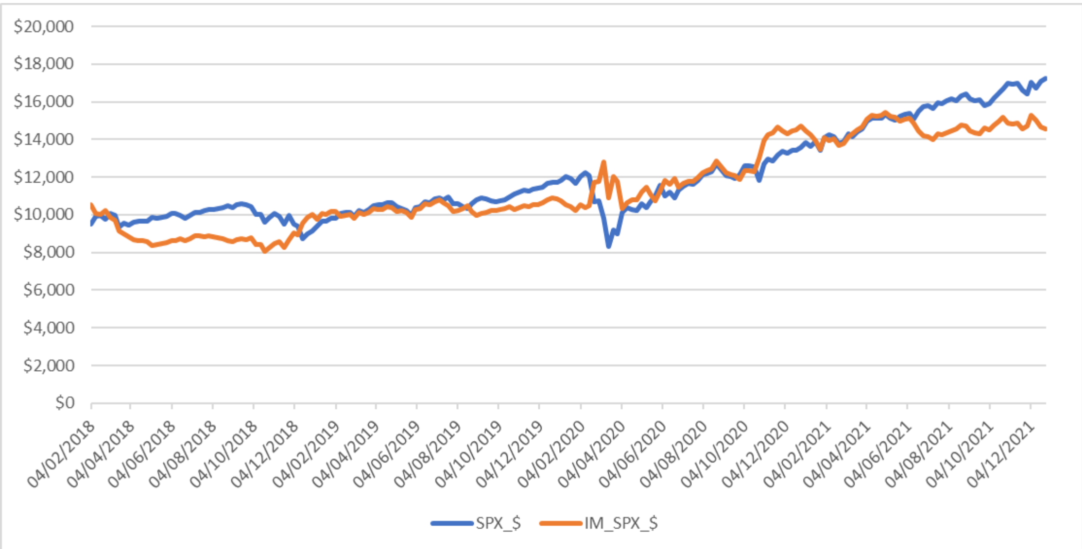

Figure 5. Prospective simulation of InvestMood trading system on S&P 500 vs the market. Source: authors own elaboration.

We observe that the evolution of the trading system and the S&P 500 are very similar. The trading system has not been able to beat the market because its evolution since June 2021.

Figure 6, like figure 5, shows the total return of the trading system prospective evolution on Bitcoin and its comparation with the evolution of the Bitcoin.

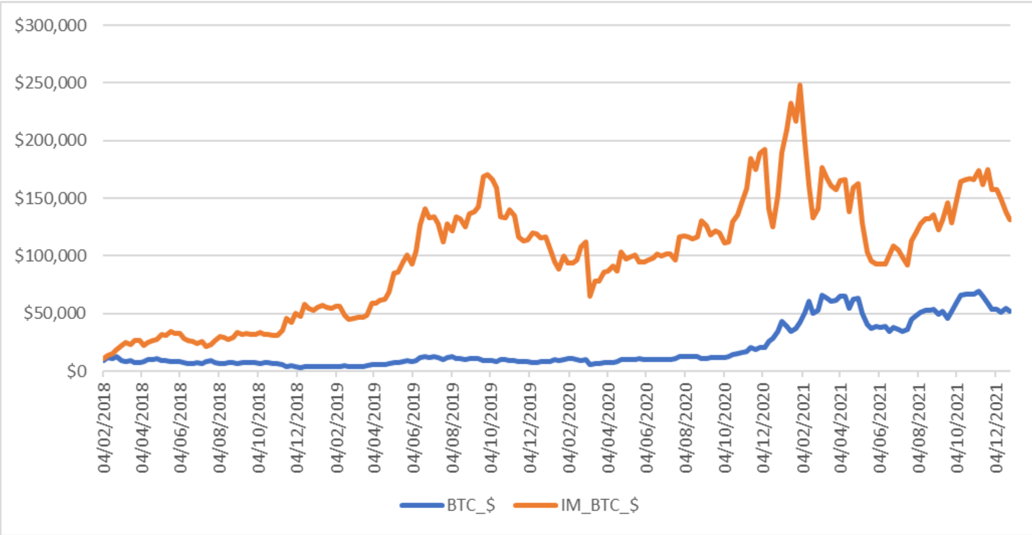

Figure 6. Prospective simulation of InvestMood trading system on BTC vs the market. Source: authors own elaboration.

In addition, we observe that the evolution of the trading system is much more profitable than the direct investment in Bitcoin.

Table 1 sums up the stats of both trading systems prospective simulation, and its comparation with S&P 500 and Bitcoin —BTC—:

Table 1. Prospective simulation of InvestMood trading system on BTC vs the market

	BTC	IM_BTC	SPX	IM_SPX
Net Return $	$ 42397.45	$ 120404.11	$ 7766.01	$ 4020.10
Net Return %	424 %	1204 %	78 %	40 %
Net Annual Return	109 %	309 %	20 %	10 %
Profit Factor	1.28	1.17	1.40	1.23
Volatility	10.59 %	10.52 %	2.77 %	2.78 %
Sharpe Ratio	10.27	29.35	7.19	3.71
Succes rate	n.a.	57 %	n.a.	53 %

Source: authors own elaboration.

So, we should highlight these points: (i) Al strategies has been profitable according to the net return; (ii) Profit factor (the ratio between win and loss) is over 1, so all the strategies have been profitable; (iii) We observe a very high Sharpe Ratios, higher for Bitcoin despite a higher volatily; (iv) An investment of 10000 USD has generated a ROI of 1204 %, if we use the signals of the AI model for BTC and a ROI of 40 %, if we use the signals of the AI model for S&P 500; (v) Success rate- (the ratio between right predictions and total predictions of the AI models) is higher for the strategy on BTC (a 57 %) than the strategy on S&P 500 (53 %). Nevertheless, both ratios are over 50 % so we assume that both are profitable.

Therefore, we should validate H1 hypothesis of this study, and it is clear that the performance of a trading strategy based on an AI model on investors' mood is better for Bitcoin than for S&P 500.

Conclusions

In this study, we used an innovative approach to check the capability of the behavioral finance and the investors' mood to predict the evolution of the financial markets, in this case S&P 500 index and Bitcoin. The study is based on big data and uses AI to predict the weekly trend of the index (up or down) and the cryptocurrency. We can check that these "pure investors' sentiment" system can be profitable both in bullish and bearish market.

First conclusion is that Google Trends is a good investors' sentiment metric. Taking into account that Google searches on economic and financial terms increase and decrease depending on the optimism or pessimism of the market, so we observe through the results of this study that this metric provides value and a certain predictive capacity.

Second conclusion from this study is that trading systems can be developed using an alternative approach to common systems based on technical analysis. This study has shown how this trading system for S&P 500 and Bitcoin is able to generate positive returns in a long/short strategy, all these operations based on the predictions of an AI model that uses investors' mood from Google Trends.

The third conclusion that we can obtain focuses on the two financial instruments analyzed. The S&P 500 is an index that shows the evolution of 500 real companies, which publish their results, and therefore, company valuation methods can be applied by calculating their theoretical price. These valuation methods cannot be applied to cryptocurrencies and their evolution is conditioned by the expectations of investors about the use of cryptocurrency and the expansion of blockchain technology. For this reason, we observe that investor sentiment is a more effective leading indicator in those instruments that are more conditioned by expectations. Therefore, investor sentiment is a better analysis tool for cryptocurrencies than for equity markets.

All this opens an interesting field of research in the development of algorithmic trading.

References

Agarwal, S., Kumar, S. and Goel, U. (2019). Stock market response to information diffusion through internet sources: A literature review. *International Journal of Information Management*, *45*(6), 118-131.

Bayes, T. (1763). An Essay towards solving a Problem in the Doctrine of Chances. *Philosophical Transactions of the Royal Society of London*, *53*, 370-418.

Berument, H., Ceylan, N.B. and Gozpinar, E. (2006). Performance of soccer on the stock market: Evidence from turkey. *The Social Science Journal*, *43*(4), 695-699.

Bouman, S. and Jacobsen, B. (2002). The Halloween indicator, "sell in may y go away": Another puzzle. *The American Economic Review*, *92*(5), 1618-1635.

Carneiro, H.A. and Mylonakis, E. (2009). Google trends: a web-based tool for real-time surveillance of disease outbreaks. *Clinical Infectious Diseases*, *49*(10), 1557-1564.

Chang, S. et al. (2012). Local sports sentiment y returns of locally headquartered stocks: a firm-level analysis. *Journal of Empirical Finance*, *19*(3), 309-318.

Choi, H. and Varian, H. (2012). Predicting the present with Google Trends. *Economic Record*, *88*, 2-9.

Cohen, G. and Kudryavtsev, A. (2012). Investor Rationality and Financial Decisions. *Journal of Behavioral Finance*, *13*(1), 11-16.

Corredor, P., Ferrer, E. y Santamaría, R. (2013). El sentimiento del inversor y las rentabilidades de las acciones. El caso español. *Revista Española de Financiación y Contabilidad*, *42*(158), 211-237.

Edmans, A., García, D. and Norli, Ø. (2007). Sports sentiment y stock returns. *The Journal of Finance*, *62*(4), 1967-1998.

Gómez, R. (2013). Señales de inversión basadas en un índice de aversión al riesgo. *Investigaciones Europeas de Dirección y Economía de la Empresa*, *19*(3), 147-157.

Gómez, R. y Prado, C. (2014). Sentimiento del inversor, selecciones nacionales de fútbol y su influencia sobre sus índices nacionales. *Revista Europea de Dirección y Economía de la Empresa*, *23*(3), 99-114.

Hilton, D.J. (2001). The Psychology of Financial Decision-Making: Applications to Trading, Dealing, and Investment Analysis. *Journal of Psychology and Financial Markets*, *2*(1), 37-53.

Hirshleifer, D. and Shumway, T. (2003). Good day sunshine: Stock returns y the weather. *The Journal of Finance*, *58*(3), 1009-1032.

Jacobsen, B. and Marquering, W. (2008). Is it the weather? *Journal of Banking & Finance*, *32*(4), 526-540.

Kaplanski, G. and Levy, H. (2010). Exploitable predictable irrationality: The FIFA world cup effect on the U.S. stock market. *Journal of Financial and Quantitative Analysis*, *45*(2), 535-553.

Leshik, E. and Crall, J. (2011). *An Introduction to Algorithmic Trading: Basic to Advanced Strategies*. New Jersey, USA: Wiley.

Liu, S. (2015). Investor Sentiment and Stock Market Liquidity. *Journal of Behavioral Finance*, *16*(1), 51-67.

Mishra, V. and Smyth, R. (2010). An examination of the impact of India's performance in one-day cricket internationals on the Indian stock market. *Pacific-Basin Finance Journal*, *18*(3), 319-334.

Moat, H.S. et al. (2013). Quantifying Wikipedia usage patterns before stock market moves. *Scientific Reports*, *3*, 1801.

Nofsinguer, J.R. (2005). Social Mood and Financial Economics. *Journal of Behavioral Finance*, *6*(3), 144-160.

Rech, J. (2007). Discovering trends in software engineering with google trend. *ACM SIGSOFT Software Engineering Notes*, *32*(2), 1-2.

Sharpe, W.F. (1994). The Sharpe ratio properly used it can improve investment management. *Journal Portfolio Management*, *21*(1), 49-58.

Yuan, K., Zheng, L. and Zhu, Q. (2006). Are investors moonstruck? lunar phases y stock returns. *Journal of Empirical Finance*, *13*(1), 1-23.

Wu, K. et al. (2013). A Big Data Approach to Analyzing Market Volatility. *Algorithmic Finance*, *2*(3-4), 241-267.