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# CNN FEAR AND GREED INDEX AS TREND SIGNAL IN GLOBAL FINANCIAL MARKETS

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ABSTRACT: Behavioral finance has shown that investor sentiment affects markets, so the challenge is to measure investor sentiment and develop investment strategies that can be profitable in any market context. For this we have developed an algorithmic trading system that takes long or short positions depending on the position of the CNN Greed & Fear index. The backtests executed, using the available historical data, provide consistent evidence of positive performance across markets, with comparatively stronger results observed in European indices, particularly the AEX.

*Keywords:* CNN Fear & Greed index, market sentiment, algorithmic trading, behavioral finance.

## 1. Introduction

Markowitz (1952) assumed that people's decisions are rational, but his perspective does not consider the influence of mood on changes in risk aversion. In this way, Finucane, Alhakami, Slovic, and Johnson. (2000), and also Nofsinger (2005) show that a good mood underestimates risk and overestimates benefit, so people in good mood are more interested in investing in risky assets.

Several studies show that different factors can change Investors' mood. Good weather causes good mood, but nasty weather causes bad mood (Goldstein, 1972; Cunningham, 1979; Sanders and Brizzolara, 1982; Howarth and Hoffman, 1984). The research in this area points out that good weather means a good mood and therefore guides investors through optimistic price stocks. Saunders (1993), Hirshleifer and Shumway (2003) found that sunshine is highly correlated with stock returns. On the other hand, sports results can also change Investors' Mood and affect stock markets. Edmans, García and Norli (2007) found a strong link between soccer outcomes and mood in international soccer results. Gomez-Martínez and Prado-Román (2014) analyzed the effect of investor mood and football national teams' results. They observed that after a victory, a positive and above-average return is recorded in the country's stock index, while the opposite occurs in a negative result.

Through investors' mood, the Moon can affect stock markets. Yuan, Zheng and Zhu (2006) and Dichev and Janes (2003) found that stock returns are significantly lower in market season around full moon, and higher returns are expected around new moon.

Superstitions, horoscopes, fortune-tellers, black cats, witches may influence individual behavior and the stock market (Kolb and Rodriguez, 1987; Dowling and Lucey, 2005; Torgler, 2007). All those effects are not totally similar in findings, but Friday 13th studies find that it is associated with below-average returns compared with other Fridays (Kolb & Rodriguez, 1987).

### *How could we measure Investors' Mood?*

Therefore, if we conclude that investors' mood affects financial markets, the challenge is how to measure mood. Darling (1955) tried to use the dividend to profit ratio to measure optimism and pessimism. Lemmon and Portniaguina (2006) used the consumer confidence survey. Linked to Internet growth and social networks, Gerow and Keane (2011) base their study on the frequency of use of different words on social networks and Moat et al (2013) studied the frequency of word use in Wikipedia. In this way, Gómez-Martínez (2013) used Internet search statistics as an indicator of the status of investor confidence showing through an econometric model that Google Trends statistics provide relevant information on the evolution of financial markets. Another attempt was made by Gómez-Martínez, Medrano-García y Gallego-Vázquez (2017) use Stockbuzz to measure Spanish Investors' Mood. Stockbuzz is a service developed by BBVA that examines Twitter messages to measure Spanish stock market sentiment. However, most of these approaches rely on indirect or survey-based measures, while fewer studies assess composite sentiment indicators within an operational trading framework.

Recent advances in sentiment measurement include the construction of composite indices from multiple data sources (Baker & Wurgler, 2007; Huang et al., 2015), the use of online search and social media data (Da, Engelberg, & Gao, 2015; Renault, 2017; Cookson & Niessner, 2020), and the integration of behavioral signals into systematic trading strategies. However, the CNN Fear & Greed Index, despite its widespread use among practitioners, has received limited empirical evaluation in academic research.

In this study we are going to focus on the Greed & Fear index published by CNN (https://edition.cnn.com/markets/fear-and-greed). CNN (Cable News Network) is an American subscription television news channel founded in 1980 by Ted Turner. Today it is part of Warner Bros. CNN was the first television network to cover news 24 hours a day and the first news channel in the United States.

As CNN describes, The Fear & Greed Index is a way to gauge stock market movements and whether stocks are fairly priced. The theory is based on the logic that excessive fear tends to drive down share prices, and too much greed tends to have the opposite effect (CNN, 2022).

As CNN describes “The Fear & Greed Index is a compilation of seven different indicators that measure some aspect of stock market behavior. They are market momentum, stock price strength, stock price breadth, put and call options, junk bond demand, market volatility, and safe haven demand. The index tracks how much these individual indicators deviate from their averages compared to how much they normally diverge. The index gives each indicator equal weighting in calculating a score from 0 to 100, with 100 representing maximum greediness and 0 signaling maximum fear.”

To avoid redundancy with existing descriptions, the seven components of the index and their signal as we can see in Table 1

Table 1. Components of the CNN Fear & Greed Index

**Components of the CNN Fear & Greed Index**

| Component | Underlying Metric | Signal Interpretation |
|---|---|---|
| Market Momentum | SP 500 vs. 125-day MA | Below MA = Fear; Above MA = Greed |
| Stock Price Strength | NYSE 52-week Highs vs. Lows | More Lows = Fear; More Highs = Greed |
| Stock Price Breadth | Trading Volume (Rising vs. Falling) | Low/Negative = Fear |
| Put and Call Options | CBOE Put/Call Ratio | Ratio > 1 (Bearish) = Fear |
| Market Volatility | VIX (50-day MA) | Higher VIX = Fear; Lower VIX = Greed |
| Safe Haven Demand | Stock vs. Bond Returns | Bonds Outperforming = Fear |
| Junk Bond Demand | Junk vs. Safe Bond Yield Spread | Wider Spread = Fear |

Source: Author’s elaboration based on CNN data

### *Theoretical Contribution and Comparison with Established Metrics*

While the VIX index (Whaley, 2000) is widely considered the "fear gauge" of the market, it focuses exclusively on implied volatility derived from S&P 500 options. Similarly, the Put/Call Ratio captures only the options market sentiment. In contrast, the CNN Fear & Greed Index provides a multi-dimensional perspective by integrating seven distinct market signals—including price momentum, breadth, and safe-haven demand into a single normalized metric (0-100).

This multi-factor approach aligns conceptually with the Baker and Wurgler (2006) sentiment index, which also aggregates multiple proxies (dividend premium, IPO volume, etc.). However, unlike Baker-Wurgler's index, which relies on monthly data and often requires orthogonalization against macroeconomic variables, the CNN Fear & Greed Index offers daily frequency and direct market observability. This makes it particularly suitable for tactical asset allocation and algorithmic trading strategies that require timely signals.

By testing this composite index across international markets (European and Asian indices), this study contributes to the literature by assessing whether a US-centric multi-factor sentiment indicator can serve as a robust global trading signal, extending beyond the single-market focus of traditional VIX-based strategies (Traub et al., 2000; Giot, 2005).

Building on this framework, this paper evaluates the CNN Fear & Greed Index as a signal generator within an algorithmic trading system applied to multiple equity indices. The objective is not to propose a new sentiment indicator, but to assess whether this widely used composite index contains actionable information when implemented in a systematic trading context.

The current value of the index is displayed on a speedometer graph as reflected in Figure 1.

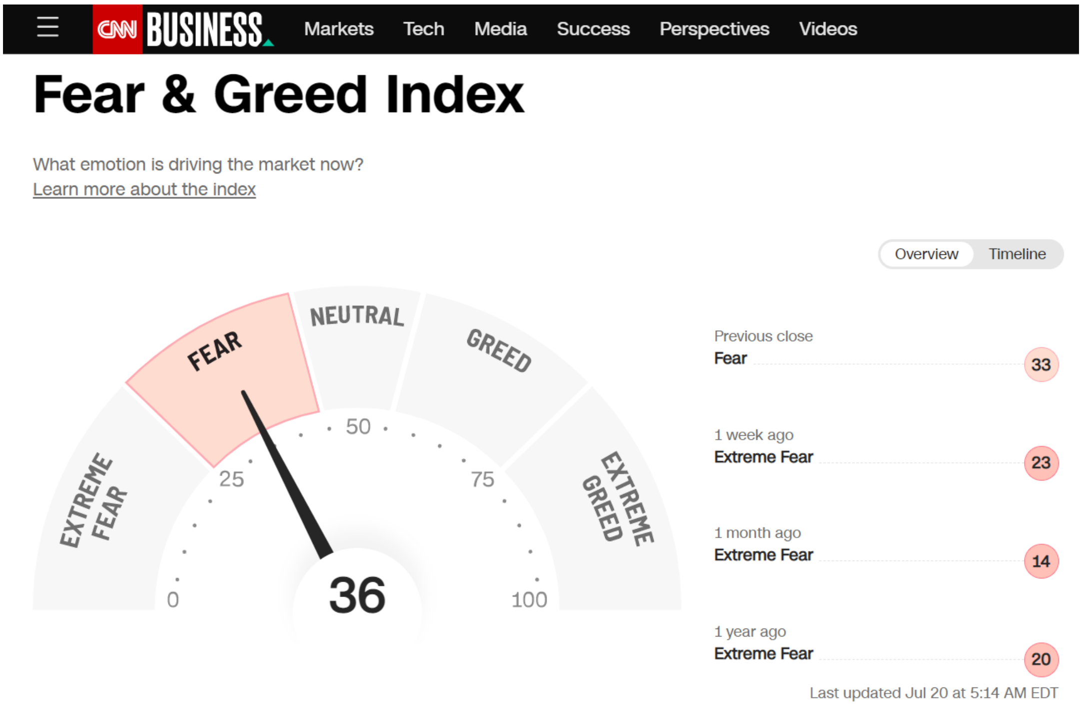


Figure 1. CNN Fear & Greed Index Overview
Source: CNN: https://edition.cnn.com/markets/fear-and-greed

Alternative shows a historical series with the daily values of the index calculated as shown in Figure 2.

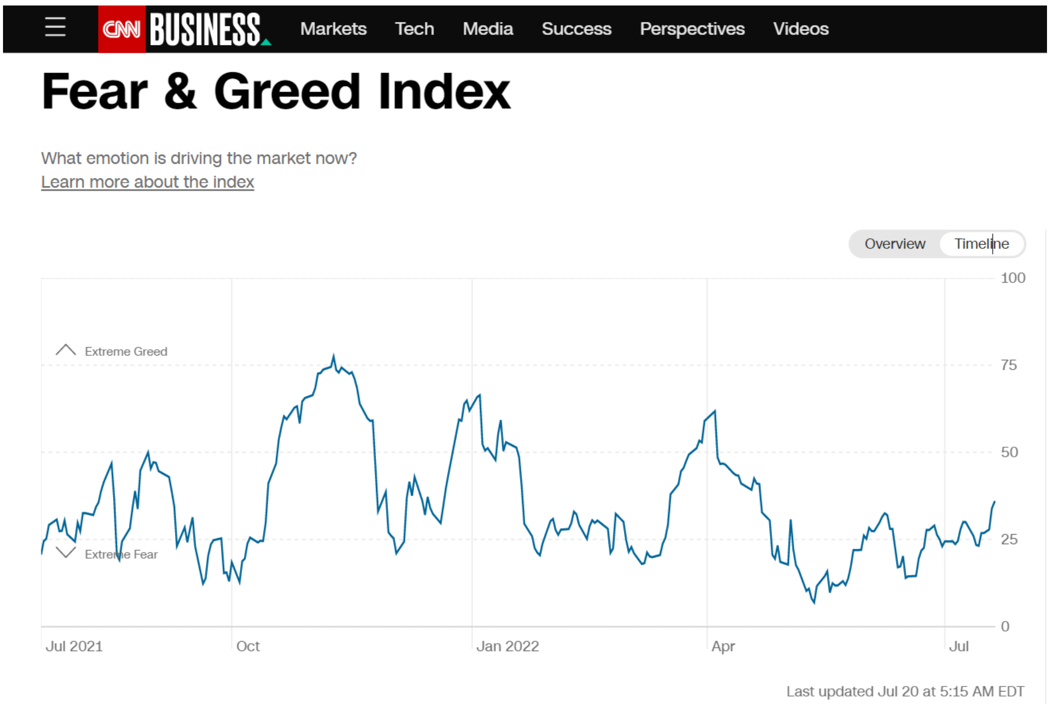


Figure 2. CNN Fear & Greed Index Timeline
Source: CNN: https://edition.cnn.com/markets/fear-and-greed

### *2. Methodology*

The assumptions that we follow are simple:

- Extreme fear can be a sign that investors are too worried. That could be a buying opportunity.
- When investors are getting too greedy, that means the market is due for a correction.

Based on these assumptions, we aim to assess the predictive capacity of this index. For this we have developed an algorithmic trading system that opens a position on Monday of each week from the last value published for the CNN Fear & Greed Index. The choice of entering the market at t+1 (Monday open) based on the index value at t (Sunday close) is a deliberate methodological decision to avoid look-ahead bias and ensure the signal is fully actionable in a real-world trading environment, rather than purely theoretical. If the published value is less than or equal to 25, we are in the "extreme fear" zone and the system will open a long position in the futures market. If, on the other hand, the signal is "extreme greed" (more than 75 points), a short position will be opened. The system will remain out of the market if the index is not at one of these two extremes.

Formally, the trading signal generation function can be expressed as follows:

$$\text{Signal}_t = \begin{cases} \text{Long} & \text{if } FG_t \leq 25 \\ \text{Short} & \text{if } FG_t \geq 75 \\ \text{Out} & \text{otherwise} \end{cases}$$

Where *FG*t represents the Fear & Greed Index value at time *t*.

These thresholds (25 and 75) represent the official definitions established by CNN for the "extreme fear" and "extreme greed" zones, respectively, as indicated on the Fear & Greed Index website (CNN, 2022).

The position is opened on Monday of week *t+1* if the signal condition is met at the close of Sunday of week *t*, and remains active until the index exits the extreme zone.

The profit and loss (P&L) for each backtest is calculated as:

$$Net\ P\&L = \sum_{i=1}^{N} [(P_{close,i} - P_{open,i}) \times M \times D_i - Costs_i]$$

where *N* is the number of trades executed, $P_{close,i}$ and $P_{open,i}$ are the closing and opening prices of trade *i*, *M* is the contract multiplier, *Di* is the trade direction (+1 for long, -1 for short), and $Costs_i$ includes commissions and slippage.

The hypothesis under analysis is:

H0: CNN Fear & Greed Index is a profitable indicator for trading.

The hypothesis is supported if the trading system delivers a positive net result over the evaluation period.

We work with a sample of weekly trading signals applied to daily futures data over a 5 years period (January 2021 – January 2026) covering different market conditions. The CNN Fear & Greed index data has been taken directly from its website. While the prices of the indices on which it has been operated have been taken from the Trading Motion platform where the systems run.

The main trend along the period for the study shows periods of bearish market conditions, as illustrated in Figure 3.


Figure 3. Market trend
*Source*: Investing

Trading Motion is a platform for automated trading strategies that has been operating in the market since 2002. Currently, this platform is connected to more than 30 brokers all over the world. Clients of these brokers can open a managed account and activate or deactivate any of the available trading systems. The platform opens for clients, in an unattended way, long or short positions, in the corresponding futures market, according to investment signals issued by the trading systems*.

The backtests have been carried out on major global equity index futures, including the American Dow Jones Industrial Average, SP 500, and Nasdaq; the European AEX, CAC 40, DAX, Euro Stoxx 50, and FTSE MIB; and the Japanese Nikkei. The comparison of performance across these markets allows us to assess which indices are more sensitive to fear and greed signals, that is, more responsive to investor sentiment indicators.

## 3. Results

The main statistics of the executed backtests are described in Table 2:

Table 2. Backtest performance

| | ESX | Nikkei | MIB | DAX | CAC | SP500 | Nasdaq | DJI | AEX |
|---|---|---|---|---|---|---|---|---|---|
| Net P&L | $7.883,02 | ¥29.492,41 | €-554,26 | €86.241,25 | €13,312,70 | $32.617,13 | $69.439,65 | $25.467,97 | €39.495,93 |
| Gross P&L | $8.000,00 | ¥30.475,00 | €-400,00 | €88.000,00 | €13.515,00 | $33.025,00 | $70.116,00 | $25.940,00 | €40.190,00 |
| Profit factor | 1,13 | 1,12 | 0,99 | 1,15 | 1,14 | 1,10 | 1,12 | 1,12 | 1,20 |
| Sharpe ratio | 0,40 | 0,40 | -0,01 | 0,44 | 0,47 | 0,33 | 0,39 | 0,38 | 0,61 |
| Annual ROI | 0,04 | 0,05 | 0,00 | 0,06 | 0,05 | 0,04 | 0,05 | 0,05 | 0,08 |
| Slippage per side | -0,27 | -4,47 | -3,51 | -1,60 | -0,46 | -0,19 | -0,77 | -2,15 | -0,08 |
| Math. expectation | 181,82 | 692,61 | -9,09 | 2.000,00 | 307,16 | 750,57 | 1.593,55 | 589,55 | 913,41 |
| Analyzed sessions | 1.148 | 1.164 | 1.144 | 1.148 | 1.154 | 1.164 | 1.164 | 1.164 | 1.154 |
| Sessions in market | 322 | 317 | 318 | 324 | 324 | 318 | 318 | 317 | 323 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| Winning sessions | 165 | 166 | 156 | 169 | 168 | 172 | 179 | 169 | 172 |
| Winning sessions % | 51,24% | 52,36% | 49,05% | 52,16% | 51,85% | 54,08% | 56,28% | 53,31% | 53,25% |
| 30 days volatility | 0,41 | 0,59 | 1,91 | 0,39 | 0,29 | 0,56 | 0,65 | 0,50 | 0,46 |
| 1 year volatility | 1,13 | 0,69 | 12,94 | 1,07 | 0,67 | 1,12 | 0,93 | 0,99 | 0,63 |
| Suggested capital | $40.000,00 | ¥120.000,00 | €50.000,00 | €325.000,00 | €55.000,00 | $200.000,00 | $320.000,00 | $120.000,00 | €105.000,00 |
| Required capital | $5.041,00 | ¥23.384,00 | €4.109,00 | €56.110,00 | €6.982,00 | $29.809,00 | $45.184,00 | $19.180,00 | €14.166,00 |

Source: Trading Motion

We observe that the majority of backtests yield positive results, with the exception of the MIB index, which shows negative performance. Overall, the evidence is consistent with the potential usefulness of the sentiment indicator across most markets analyzed. While these results are encouraging, they should be interpreted with caution given the absence of formal statistical benchmarks at this stage, a limitation that is further addressed in the discussion section.

Since the futures used in the study have different multipliers and margin levels, we cannot directly compare gross or net profit and loss. We must therefore look at the ROI of the backtest, which is calculated as the ratio between the net profit and the suggested capital. The suggested capital is the one recommended by the Trading Motion platform to operate with the system without it being canceled due to lack of guarantees. However, the guarantees requested by the market are lower and are expressed in the required capital. We explicitly utilize this 'Suggested Capital' metric as the ROI denominator to standardize leverage across heterogeneous futures contracts, ensuring a fair cross-market comparison despite differing contract multipliers and margin requirements.

Within this general positive performance, the system executed on the Dutch AEX index exhibits the highest performance metrics among the analyzed markets, including ROI (8.35%), profit factor (1.20), and Sharpe ratio (0.61).

We can see the P&L chart in Figure 4.

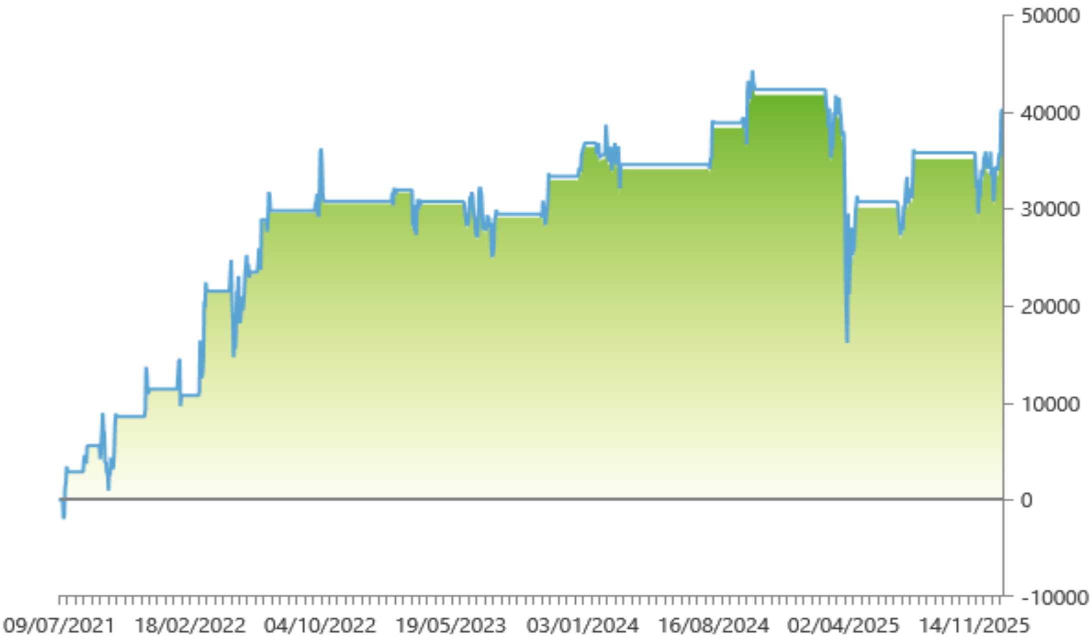


Figure 4. P&L chart AEX backtest
*Source*: Trading Motion

On the other hand, the MIB index shows negative performance across all metrics. The MIB P&L chart is shown in Figure 5.

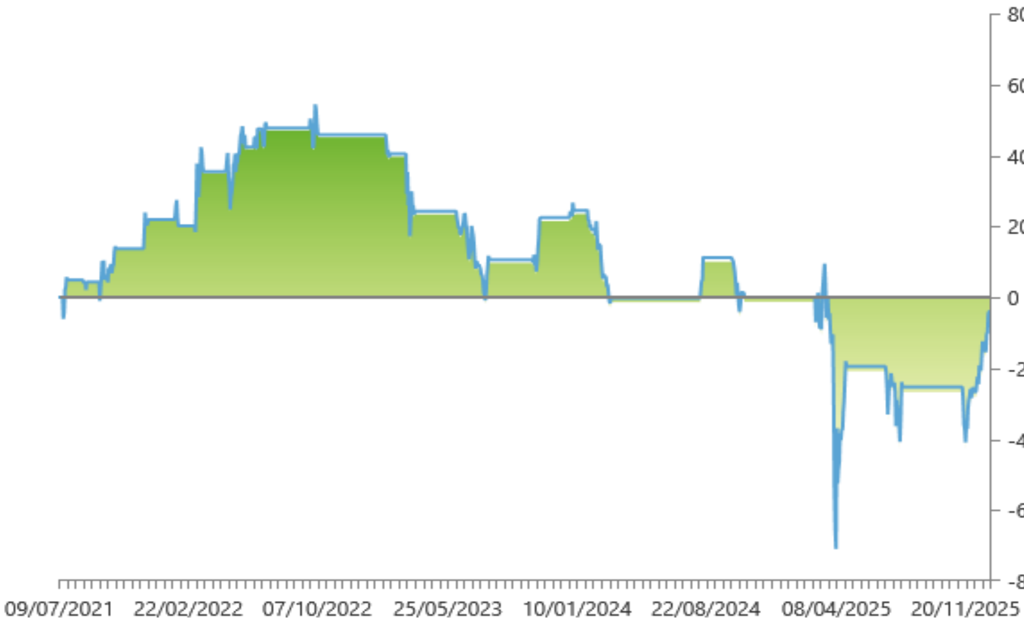


Figure 5. P&L chart MIB backtest
Source: Trading Motion

***4.- Conclusion, discussion and implications.***

In this paper we have reviewed that stock markets are not as rational as traditional theory on market efficiency told us. The development of research in neuroeconomics and in the field of behavioral finance have shown that mood influences investment decisions, and therefore the market trend. Proof of this is all the evidence found on external factors that condition investors' mood and therefore affect the markets. Among them we can highlight sports results, lunar phases or even superstitions.

Keeping this in mind, the challenge is how to measure investor sentiment to anticipate the market and build profitable investment strategies, both in bullish and bearish markets. Several authors have faced this challenge using consumer confidence surveys, information from social networks such as Twitter, or what is searched on the Internet using Google Trends. In this paper we assess an approach using CNN's Fear & Greed index as the "engine" of an algorithmic swing trading system.

The algorithmic trading system consults the index every Sunday and opens a long position on Monday if the index is in the "extreme fear" position or short if the index is in the "extreme greed" position. The position remains in the market until the index leaves this position, if the index is not at these extremes, the system remains out of the market.

Multiple backtests of the system have been carried out over a 5 year period (2021-2026) on major equity index futures including the American Dow Jones, SP 500, and Nasdaq; the European AEX, CAC 40, DAX, Euro Stoxx 50, and FTSE MIB; and the Japanese Nikke. The majority of backtests yield positive results, with the exception of the MIB index. Overall, the evidence is consistent with the potential usefulness of the Fear & Greed Index as a sentiment-based trading signal.

Regarding the success rate (approx. 52-60%), it is consistent with trend-following strategies which typically rely on asymmetric payoffs rather than high hit rates. The fact that the Profit Factor remains > 1.20 demonstrates that the system generates alpha by capitalizing on the magnitude of trends, not just their frequency.

Comparing performance across markets, the highest metrics are observed in the AEX index, despite the Fear & Greed Index being constructed exclusively from U.S. market data. This suggests that sentiment signals may have cross-market applicability, although the reasons for differential performance across indices require further investigation.

Future studies could compare the Fear & Greed Index with established sentiment measures such as the Baker-Wurgler index or VIX-based indicators to assess relative predictive power.

This study has important limitations. While the extended evaluation period strengthens the robustness of the findings compared to shorter samples, out-of-sample validation and comparison with alternative sentiment indicators remain as necessary extensions. Future research could also explore the combination of the Fear & Greed Index with other sentiment measures and assess performance across different market regimes.

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