The CNN Fear and Greed Index as a Predictor of US Equity Index Returns

Hugh Farrell[1] and Fergal O'Connor[2]

Abstract

We assess whether the CNN "Fear and Greed" Index can be used to predict returns on equity indices and gold using hand-collected data. We find that the Fear and Greed Index Granger causes returns on the S&P 500, Nasdaq Composite and Russell 3000 indices in the first sample period (2011-2020), but not gold returns. Analysis from 2021–2024 indicates the Fear and Greed index Granger causes S&P 500 and Russell 3000 returns, but the relationship is considerably weaker. No significant relationship is found between the VIX and stock indices, indicating that the Fear and Greed Index is a better predictor of equity returns.

Competing interests: The authors declare none.

Keywords: Fear and Greed, Granger Causality, Equity Indices, VIX, Gold.

JEL Codes: G4, G10, G11, G12, G15

[1] Corresponding author, Cork University Business School, HFarrell@ucc.ie, Aras Na Laoi, Gaol Walk, Cork, Ireland T12 K8AF; +353 (0)21 490 3000

[2] Cork University Business School, fergal.oconnor@ucc.ie

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Introduction

The Fear and Greed Index, created by CNN Business, is an attempt to characterise the overall sentiment of the equity market, based on the premise that these two emotions drive the market from day to day. In this paper, we test whether the Fear and Greed index is a useful tool to predict future asset returns. To this end, we run Vector Autoregressive Models (VAR) with the Fear and Greed (FG) Index and the returns on three stock indices and gold.

At present, the literature looking at the FG Index is quite sparse. Gómez-Martínez et al. (2023) utilise weekly FG Index data from July 2021 to June 2022 to create an algorithm to trade on various indices. They find that the system they develop is profitable over all the indices they tested. Johnson (2023) estimates the Spearman correlation between the FG Index and five US stock indices, finding a positive relationship between the indices and higher values of the FG Index for all. Liutvinavičius et al. (2017) created a FG Index similar to that provided by CNN and found that strategies based on this index can be used to prevent losses.

A separate but related literature focuses on the relationship between cryptocurrencies and FG Indices. Gunay et al. (2022) find that a crypto FG Index, as well as the VIX can be used to predict reversals in bull markets. Łęt et al. (2022) find that strategies using a crypto FG Index lead to significantly better performance than passive crypto investing. Cavalheiro et al. (2024) find a linear relationship between the CNN FG Index and Bitcoin and Ethereum returns. Gaies et al. (2023) test for Granger causality between a crypto FG Index and Bitcoin prices, finding periods with negative interactions and periods with positive interactions.

Using daily data collected from the CNN website and the Wayback Machine Archive, we find that the FG Index can be used to predict returns for the three equity indices. We also assess the FG Index's ability to predict asset returns other than equities using gold prices which have a different market structure to equities (see O'Connor et al. (2015) for a review of the literature on gold). We find that the FG Index is unable to predict gold returns. Furthermore, this predictive power changes over time, with more significant results in the earlier period analysed. While the FG Index can predict returns, it is unlikely that trading strategies based on the index will be profitable, due to the small size of the VAR coefficients.

The remainder of the paper is structured as follows: Section 2 outlines the data collected and the methods of analysis used, Section 3 shows the results of our analysis and Section 4 presents our conclusions.

Data and Methodology

For this analysis, we examine a total of six variables across two time periods. Data on the FG Index was obtained from two separate sources. From 03/01/2011 to 18/09/2020 the values come from a repository on GitHub, where they were scraped from the CNN Business website (Furmanski, 2022) and from 07/04/2021 to 08/03/2024 we take data from the CNN website using the Wayback Machine. This site allows users to examine historical archived versions of webpages. In our case, it shows a total of one year of values for the FG Index for their webpage. Data is unavailable for the in between period and for this reason, we analyse both periods separately.

The Fear and Greed Index is calculated by CNN Business and takes on values between 1 and 100, where 1 indicates extreme fear, 100 indicates extreme greed.

Lower values of the index indicate the market is on average fearful whereas higher values indicate the market is greedy. This index is calculated as a simple average of seven factors; Market Momentum, Stock Price Strength, Stock Price Breadth, Ratio of Put to Call Options, Market Volatility (VIX), Safe Haven Demand and Junk Bond Demand. Values between 03/01/2011 to 18/09/2020 are taken from a repository on GitHub, values from 08/03/2023 and 08/03/2024 are taken directly from the CNN Business website while values from 07/04/2021 to 07/03/2023 are taken from the CNN Business website using the Wayback Machine. Tables 1-2 summarise the data for each of our six variables for the two sample periods. All returns are calculated as log returns.

Table 1: Summary Statistics 2011 - 2020

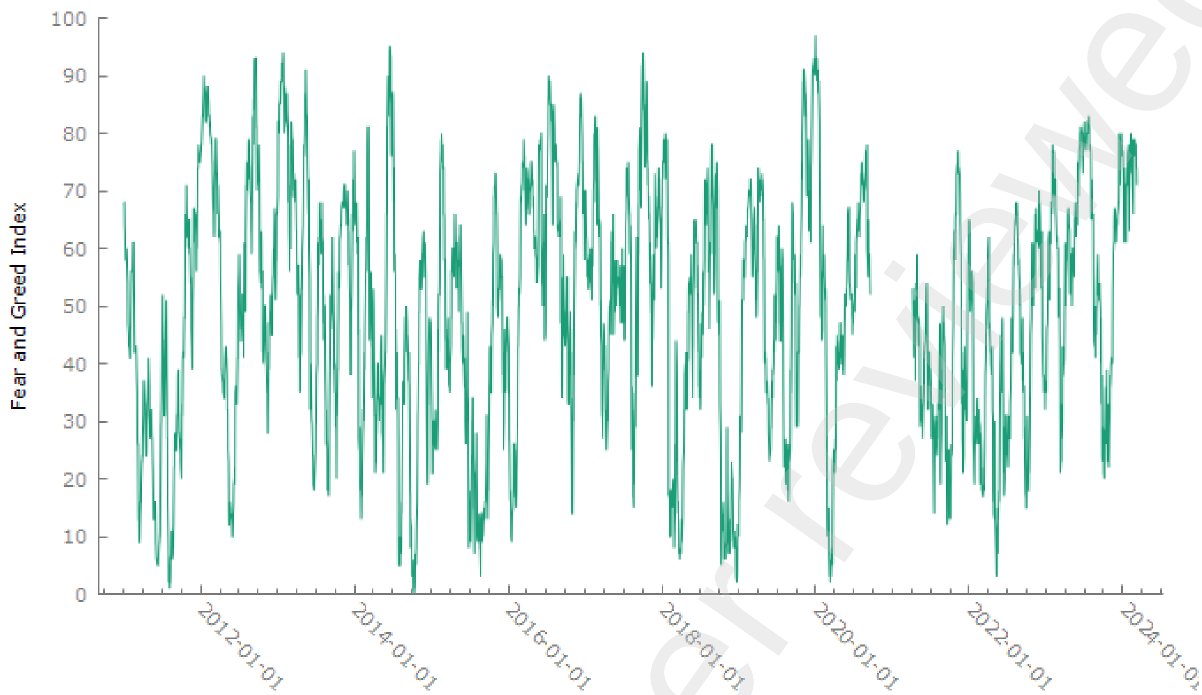
	Fear and Greed	S&P500 Returns	Nasdaq Returns	Russell 3000 Returns	LBMA Gold Returns[1]	VIX (Full Sample)
Obs.	2445	2445	2445	2418	2392	3316
Mean	49.31	0.00022	0.00023	0.00019	0.00010	18.205
Median	52	0.00053	0.00079	0.00072	0.00019	16.285
Skewness	-0.214	-0.529	-0.520	-1.425	-0.585	2.478
Ex. Kurtosis	-0.795	6.867	4.446	18.820	7.068	11.426

Table 2: Summary Statistics Q2 2021 – Q1 2024

	Fear and Greed Index	S&P500 Returns	Nasdaq Returns	Russell 3000 Returns	LBMA Gold Returns
Obs.	736	736	736	734	707
Mean	47.658	0.0002	0.0002	0.0002	0.0002
Median	47	0.0004	0.0006	0.0004	0.0002
Skewness	0.002	-0.182	0.006	-0.248	-0.117
Ex. Kurtosis	-1.078	1.418	1.965	1.357	1.741

[1] Many gold markets operate throughout the world, but the London and New York markets have been shown to be dominant in price discovery, see Lucey et al. (2014).

Figure 1: Fear and Greed Index from Q1 2011 – Q3 2020



Source: 2011-2020 Furmanski (2022), 2021 – 2024 CNN Business via https://wayback-api.archive.org/

To ensure stationarity, we run Augmented-Dickey Fuller (ADF) tests on all variables for both time periods. The results of these tests are presented in Table 3. The ADF tests for all variables in both time periods are significant at the 1% level, indicating that all variables are stationary.

Table 3: Augmented Dickey-Fuller Tests

Variable	**Test Statistic (*2011 – 2020)***	**Test Statistic (*2021 – 2024)***
Fear and Greed	-6.028***	-3.554***
S&P 500 Returns	-11.50***	-17.20***
Nasdaq Returns	-13.81***	-17.43***
Russell 3000 Returns	-10.27***	-27.02***
LBMA Gold Returns	-49.26***	-10.59***
VIX (Full sample period)	-5.617***	

****, ** and * indicate significance at the 1%, 5% and 10% levels respectively.*

We then carry out several Vector Autoregressive Models (VAR) to ascertain the predictability of asset returns from values of the Fear and Greed Index. We use the Akaike Information Criterion (AIC) to determine the optimal lag structure of each VAR model. For each of the two time periods we run a total of four VARs, one for each of the stock indices and gold returns with the FG Index included in each. We then repeat this procedure exchanging the absolute value of the FG Index for the log difference of the FG Index. The VAR model we use is as follows:

$$\Delta y_t = \alpha_0 + \sum_{i=1}^{k} \alpha_{1i} \Delta y_{t-i} + \sum_{i=1}^{k} \alpha_{2i} FG_{t-i} + \varepsilon_{1t} \quad (1)$$

$$\Delta FG_t = \alpha_0 + \sum_{i=1}^{k} \alpha_{1i} \Delta FG_{t-i} + \sum_{i=1}^{k} \alpha_{2i} y_{t-i} + \varepsilon_{2t} \quad (2)$$

Where y_t represents the returns on the indices/gold at time *t* and FG_t represents the value of the Fear and Greed index at time *t.*

We then run three more VARs, assessing if the VIX can be used to predict the returns of the three stock indices. We do this to determine if the FG Index predictive power is independent of the VIX or whether any results from the initial models are purely driven by volatility and to compare the effectiveness of the FG index to the VIX for predictive purposes. As data is available on the VIX for the entire time period, we run the model using the entire set of data from 03/01/2011 - 08/03/2024. For all of the VAR models above we use Heteroscedasticity and Autocorrelation Consistent (HAC) errors.

Finally, we carry out Granger causality tests for each of the above VAR models to determine whether FG/VIX Granger causes asset returns and vice versa.

Results

Table 4 shows the results of the Granger causality tests between FG and asset returns. We test for causality in both directions, FG Granger causing returns and returns Granger causing FG. For the first subperiod, we find that FG Granger causes all stock index returns, with a relationship which is significant at the 1% level. Index returns are also shown to Granger cause FG, but the relationship is slightly weaker.

No significant relationship is found between gold returns and FG which fits well with He et al. 's (2018) findings that at a daily level, there is no relationship between equity and gold markets. The results are less clear for the second subperiod. We see that FG Granger causes S&P 500 returns and Russell 3000 returns but does not Granger cause Nasdaq returns. Furthermore, the F-tests in the second period are much less significant, partially due to the lower number of observations available.

Table 4: Granger Causality Tests between the Equity Indices, Gold and FG

	Direction of Causality (Lag)	**Q1 2011-Q3 2020 F-Value**	**Q2 2021-Q1 2024 F-Value**
S&P 500	FG >> Return (4)	15.35***	2.053*
	Return >>FG (4)	2.972**	2.586*
Nasdaq	FG >> Return (4)	11.35***	1.231
	Return >>FG (4)	2.965**	3.439**
Russell 3000	FG >> Return (4)	16.6***	2.002*
	Return >>FG (4)	3.268**	3.42***
LBMA Gold	FG >> Return (4)	0.611	1.383
	Return >>FG (4)	0.939	1.999*

****, ** and * indicate significance at the 1%, 5% and 10% levels respectively.*

Table 5 shows the results of the Granger causality tests where the absolute value of the FG Index is changed to the log of the first differences of FG. In the first period, the log difference of FG Granger causes returns for the three equity indices, significant at the 1% level. There is also a relationship in the opposite direction, equity returns Granger cause log differences in FG, but with lower significance. Again, there is no relationship between FG and gold. In the second period, we see that the log difference of FG does not Granger cause any of the equity index returns but returns Granger cause FG.

The differences between the two time periods imply that the relationship between FG and returns is not consistent over time, as the relationship in later years appears to be much weaker.

Table 5: Granger Causality Tests between indices/gold and log change in FG

	Direction of Causality (Lag)	**Q1 2011-Q3 2020 F-Value**	**Q2 2021-Q1 2024 F-Value**
S&P 500	FG >> Return (4)	12.00***	0.136
	Return >>FG (4)	2.287*	3.311**
Nasdaq	FG >> Return (3)	12.22***	0.098
	Return >>FG (3)	2.714**	3.017**
Russell 3000	FG >> Return (4)	6.167***	0.149
	Return >>FG (4)	2.946**	2.065*
LBMA Gold	FG >> Return (4)	0.612	1.672
	Return >>FG (4)	0.944	1.28

****, ** and * indicate significance at the 1%, 5% and 10% levels respectively. Lags were chosen based on the AIC for the first model, maximum four lags.*

Table 6 shows the results of the VAR models for the equity indices when we take the absolute value of the FG index. In the first period we see that the first lag of FG is positively and significantly related to returns for all three indices. The second lag is significant and negative for the Russell and S&P 500, but not for the Nasdaq, while the third lag is significant and negative for all three indices. For the second period, while the sign of the first lag is positive for all three, it is not a significant predictor. For the three indices, the third and fourth lag of FG are significant, with the third lag positive and the fourth negative for each. The second lag is only significant for the Nasdaq.

We should note that the sign of the third lag has changed from the first period to the second. Also, the significant results of the Granger causality tests from the second period appear to be mainly driven by the third and fourth lag, whereas the strongest predictor from the first period is the first lag.

Table 6: VAR with S&P 500 returns and absolute value of the Fear and Greed Index.

	Q1 2011-Q3 2020			Q2 2021-Q1 2024		
	S&P 500	**Nasdaq**	**Russell**	***S&P 500***	**Nasdaq**	**Russell**
Lag 1	0.0004***	0.00026***	0.0004***	0.0001	0.0001	0.0001
Lag 2	-0.0002**	0.0001	-0.0002***	-0.0002	-0.0003*	-0.0003
Lag 3	-0.0001**	-0.0002***	-0.0002***	0.0003**	0.0003**	0.0003**
Lag 4	-0.0004	0.0001	0.0001	-0.0002**	-0.0002*	-0.0002**

****, ** and * indicate significance at the 1%, 5% and 10% levels respectively.*

Table 7 shows the results of the VAR models with the equity indices when we take the log difference of FG. In the first period the first two lags are significant and positive for all, implying an increase in the FG index is followed by an increase in equity returns. In the second period none of the lags are significant for any of the indices.

Table 7: VAR with S&P 500 returns and log change of the Fear and Greed Index

	Q1 2011-Q3 2020			Q2 2021-Q1 2024		
	S&P 500	**Nasdaq**	***Russell 3000***	***S&P 500***	***Nasdaq***	**Russell 3000**
Lag 1	0.0093***	0.0069***	0.0086***	0.0023	0.0012	0.0028
Lag 2	0.0068***	0.0067***	0.0059***	-0.0012	-0.0016	-0.0014
Lag 3	0.0051**	0.0025	0.0041	0.0014	0.0016	0.0002
Lag 4	0.0002	-	-0.0004	0.0007	-	-0.0006

****, ** and * indicate significance at the 1%, 5% and 10% levels respectively.*

A key question raised by these results is whether or not we can leverage this information to engage in profitable trades. The results imply that both a high value of the FG and a positive change in FG are followed by higher returns in equity markets. It may be possible to buy indices when FG is high or when there is a large one-day increase and earn profits. However, the size of the VAR coefficients suggests this is unlikely to be the case. For example, a one-unit increase in today's FG value is predicted to lead to a 0.04% increase in S&P 500 returns tomorrow per Table 7. A 30-point increase in the FG index would then equate to just over a 1% increase in returns. Such small numbers from an index bound between 1 and 100 implies that any profits one could earn would be more than wiped out by transaction costs.

Table 8: Granger Causality Tests between The Equity Indices and VIX

	Direction of Causality (Lag)	**F-Value**
S&P 500	VIX >> Return (4)	0.744
	Return >>VIX(4)	1.461
Nasdaq	VIX >> Return (2)	1.953
	Return >>VIX (2)	0.465
Russell 3000	VIX >> Return (4)	1.542
	Return >>VIX (4)	0.762

****, ** and * indicate significance at the 1%, 5% and 10% levels respectively.*

Finally, Table 8 tests whether the VIX Granger causes returns on the equity indices. We include such results as a point of comparison between the VIX and FG index and to analyse whether the significant results from the FG index are driven by changes in volatility. We can see that the VIX does not Granger cause any of the index returns. This implies firstly that the significant results from the FG models are not driven solely by the VIX and secondly that the FG Index is a better predictor of index returns than the VIX.

Conclusion

We find that the CNN Business Fear and Greed index can be used to predict future asset returns. Firstly, the absolute value of FG is a strong predictor of returns in the first, and longer, sample period analysed, and while there are still some significant results in the second period, they are not as convincing. Secondly, a change in the index can also be used to predict returns, but these results are only significant in the longer first sample period.

Two aspects of our results cast doubt on the possibility of these results allowing traders to implement trading strategies that would lead to profitable results. Firstly, our results are less significant in the later (shorter) sample period, which may point to a weakening of the relationship between the FG Index and stock returns over time. Secondly, the VAR coefficients are quite small, meaning any excess returns are likely to be wiped out by fees and other transaction costs. Further research may be required to ascertain whether there is any possibility of using the FG Index to trade profitably.

From our tests, it is also clear that it is not simply the volatility index portion of the composite FG index which is driving our results, and the FG Index is shown to be a superior predictor than the VIX. We find no predictive power of the VIX for any of the equity indices.

Future research building on the ideas of this paper could focus on extending the analysis to further asset classes, such as bonds, derivatives, international stock indices and metals. The FG Index could also be split into seven constituent parts to ascertain which of these parts drive the results seen in our analysis or if they are greater than the sum of their parts in predictive power.

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