Financial Navigator Journal	Digital Finance Conference
Vol. 1, no. 1, May 2025	**Selected Edition**

Gergana Taneva-Angelova and Stefan Raychev

Fear Regimes in DeFi: A Study of Investor Behavior and Market Dynamics

Gergana Taneva-Angelowa (G.T-A.), Ph.D., is an Associate Professor at the Department of Finance and Accounting, University of Plovdiv "Paisii Hilendarski". Contact: gergana.taneva@uni-plovdiv.bg.

Stefan Raychev (S.R), PhD, is an Associate Professor at the Department of Economic Sciences, University of Plovdiv "Paisii Hilendarski,". Contact: stefan.raychev@uni-plovdiv.bg.

Abstract The aim of this study is to analyze how fear affects investor behavior in decentralized financial (DeFi) markets. The focus is on the relationship between the Fear and Greed Index (F&G) and the market prices of governance tokens from major DeFi platforms, including PancakeSwap, Balancer, Compound, SushiSwap, Uniswap, Aave, and MakerDAO. Each of these tokens is a native asset linked to a specific DeFi protocol and, beyond their tradability, they function as governance instruments, making them particularly sensitive to shifts in market sentiment and investor expectations. To examine how investor fear and greed impact token price dynamics, we apply a combination of econometric and behavioral approaches. Our findings suggest that while investor sentiment may influence volatility and regime shifts, its direct predictive power over daily returns of governance tokens remains weak.

Keywords DeFi, Fear Regimes, Investor Behavior, Governance Tokens, Fear and Greed Index.

DOI: https//doi.org/10.56065/FNJ2025.1.36

Introduction

Over the past decade, decentralized finance (DeFi) has emerged as a key innovation in the digital economy, providing a wide array of financial services – such as borrowing against crypto collateral on platforms like Aave, Compound, and MakerDAO, ot peer-to peer trading via liquidity polls on Uniswap, PancakeSwap, and Balancer – all built on decentralized networks that eliminate traditional intermediaries. Central to these systems are governance tokens - such as UNI, MKR, AAVE, BAL, COMP, and CAKE - which grant holders voting rights over protocol decisions and often come with economic incentives like yield farming and staking (Harvey et al., 2021). While these tokens are actively traded and subject to market speculation, their governance function ties them closely to the long-term stability and evolution of DeFi protocols. However, because they are freely traded, they are also exposed to speculative pressure and short-term sentiment-driven volatility, especially during uncertain market conditions. Therefore, it is important to assess whether governance tokens remain resilient to sentiment shifts or are influenced by emotional trends. Investor sentiment, which is shaped by emotions such as fear, uncertainty, and greed, often drives market dynamics and creates conditions known as fear regimes, characterized by panic selling, heightened volatility, and risk aversion. These regimes often trigger herding behavior, where investors follow the majority instead of relying on

Vol. 1, no. 1, May 2025

independent analysis (Bouri et al., 2019; da Gama Silva et al., 2019), with common patterns including FOMO (Fear of Missing Out) during bull markets and FUD (Fear, Uncertainty, Doubt) in response to negative events, such as hacks or regulatory news (Zizheng and Yuen, 2023). In the DeFi market, such sentiment-driven behavior can distort token prices and market dynamics, reinforcing the need to study how these psychological effects interact with DeFi governance structures. This study investigates how sentiment affects governance tokens in DeFi by applying the Fear and Greed Index (F&G Index), a behavioral measure of market mood widely used in crypto markets. As sentiment reflects emotional extremes - such as panic selling or speculative buying - it may play a role in driving market reversals. Since governance tokens combine tradability with protocol-level influence, they may be especially sensitive to shifts in sentiment and volatility. Although behavioral finance (BeFi) literature has explored emotional drivers in crypto and DeFi markets (Schär, 2021; Bennett et al., 2023; Bouri et al., 2019; Al-Mansour, 2020), there is limited research on how sentiment specifically affects governance tokens (Radu & Deak, 2024; Albrecht et al., 2023; Teplova et al., 2023).

The aim of this paper is to empirically assess whether daily sentiment shifts, measured by FNG_ret (returns of the F&G Index), predict the daily logarithmic returns (PS_ret) of governance tokens. Our focus is on understanding if broader crypto market sentiment affects DeFi tokens, which are structurally distinct and driven by protocol-level mechanisms. The lack of centralized regulation and the presence of emotion-driven decision-making amplify risk in DeFi, making the influence of fear and greed particularly relevant. As behavioral patterns complicate financial forecasting (Gusev, 2018), it is essential to include sentiment indicators when studying DeFi token dynamics, especially given the prevalence of non-professional and emotionally reactive investors (Al-Mansour, 2020). To meet this goal, we collected data on six leading governance tokens and used both classical econometric and machine learning methods to test for the impact of sentiment. This multi-method approach allows us to capture both linear and nonlinear effects, as well as regime-specific behavior under sentiment-driven market conditions. The paper proceeds as follows: section 2 reviews the relevant literature, section 3 presents the methodology, and section 4 discusses the empirical results.

1. Related work

Recent research on decentralized finance (DeFi) has established a strong theoretical foundation for understanding its benefits, risks, and structural features (Harvey et al., 2021; Erya Jiang et al., 2023; Bennett et al., 2023). Studies highlight the influence of market sentiment, investor psychology, and the systemic vulnerabilities of DeFi, including high volatility, lack of regulation, and protocol-level risks (Schär, 2021; Barbereau et al., 2022). One major concern is the concentration of governance power in the hands of a small group of participants, which undermines decentralization and increases the potential for manipulation and panic during market shocks. The volatility of crypto collateral in DeFi protocols

Vol. 1, no. 1, May 2025

can trigger rapid liquidation risks, while the absence of consumer protections amplifies behavioral patterns such as herding and overconfidence (Al-Mansour, 2020; Poyser, 2018). Herding behavior, as noted by da Gama Silva et al. (2019), Bouri et al. (2019), and Poyser (2018), often arises during periods of uncertainty and negative news. Prospect Theory (Kahneman and Tversky, 1979) shows that fear of losses strongly influences decision-making, contributing to price distortions and speculative bubbles (Al-Mansour, 2020). Psychological factors are particularly significant in emerging technologies like DeFi (Bennett et al., 2023; Bouri et al., 2019; Shu & Chang, 2015). In many protocols, governance tokens are centrally held by core teams or large investors, creating risks of market manipulation and weakening the democratic integrity of DeFi governance (Bhambhwani, 2025; Dang & Dewally, 2023). As a result, some DeFi projects are more susceptible to behavioral distortions than others. Empirical research confirms that investor sentiment, especially as shaped by collective opinion, social media, and emotional attachments to digital assets, plays a substantial role in speculative environments (Gusev, 2018; Shen et al., 2019; Liu & Tsyvinski, 2021; Baker & Wurgler, 2006). While the role of behavioral finance in crypto markets is well-established, the present study adds to this literature by specifically examining how fear and greed affect DeFi governance tokens, using a multi-method approach designed to capture both linear and nonlinear dynamics.

2. Data Collection

This study focuses on six leading DeFi protocols - Aave (01.02.2018–06.03.2025, n=2741), Maker (01.02.2018–06.03.2025, n=2545), Compound (18.08.2020–06.03.2025, n=1660), Uniswap (14.09.2020–06.03.2025, n=1269), PancakeSwap (14.09.2021–06.03.2025, n=1269), and Balancer (22.07.2021–06.03.2025, n=1330) - as these governance tokens are highly liquid, cover a range of functional areas within the DeFi ecosystem, and play a central role in protocol operations. The variation in data periods (2018–2025) enables sentiment analysis across different DeFi market phases, from early development to maturity. Governance token data were sourced from Investing.com, while sentiment data were obtained from Alternative.me’s Fear and Greed Index, which reflects market mood using inputs such as volatility, trading volume, social media, surveys, and Google Trends. Index values above 50 indicate greed (risk-seeking behavior), below 50 signal fear (risk aversion), and 50 represents neutrality. Data analysis was conducted in Python 3.13 using standard libraries including pandas, numpy, statsmodels, arch, scikit-learn, xgboost, pywt, dcor, and minepy.

3. Methodology

The methodology adopts a multi-model framework designed to assess both linear and nonlinear relationships between the Fear and Greed Index (FNG_ret) and DeFi governance tokens. The null hypothesis is H_0: FNG_ret has no statistically significant effect on daily log returns or regime-switching probabilities of the tokens. To explore this, we implement a

Vol. 1, no. 1, May 2025

sequence of statistical and machine learning models. We begin with correlation and cross-correlation analyses, followed by OLS regression to quantify linear dependence:

$$Token_{ret_t} = \beta_0 + \beta_1 FNG_{ret_t} + \varepsilon_t \tag{1}$$

where: β_1 captures the average return response to a 1% change in the index. The model was evaluated using RMSE, MAE и R^2. Granger causality tests (lags 1 to 10) are then applied to identify temporal causality, with the null rejected if p < 0.05:

$$Y_t = \beta_0 + \sum_{i=1}^{p} \beta_i Y_{t-1} + \sum_{j=1}^{p} \gamma_j X_{t-j} + \varepsilon_t \tag{2}$$

ARIMAX model are used to capture dynamic dependencies, with FNG as an exogenous regressor:

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \sum_{j=1}^{q} \theta_j \varepsilon_{t-1} + \sum_{k=1}^{K} \beta_k x_{k,t} + \varepsilon_t \tag{3}$$

where ϕ and θ represent AR and MA terms, and $\beta_k x_{k,t}$ incorporates the effect of FNG. To capture volatility dynamics, GARCH (1,1) and GJR-GARCH (1,1,1) models are estimated:

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \tag{4}$$

$$\sigma_t^2 = \omega + \alpha \epsilon_{t-1}^2 + \beta \sigma_{t-1}^2 \pm \gamma I\{\varepsilon_{t-1} < 0\} \varepsilon_{t-1}^2 \tag{5}$$

where γ measures asymmetry in response to negative shocks. Markov Switching Regression identifies latent volatility regimes - allowing the assessment of sentiment effects across low and high volatility states.

$$y_t = \mu S_t + \varepsilon_t \; S_t \in \{0,1\} \tag{6}$$

$$p_{ij} = P(S_t = j \mid S_{t-1} = i) \tag{7}$$

To detect nonlinear dependencies, we apply the Maximal Information Coefficient (MIC):

$$MIC(X,Y) = \frac{max_{(x,y)}\{I*(X,Y;x_{bins},y_{bins})\}}{\log \min\{x_{bins},y_{bins}\}} \tag{8}$$

where: MIC ∈ [0, 1] measures the strength of association without assuming linearity. We also implemented Support Vector Regression (SVR) with an RBF kernel:

$$f(X) = \langle w, X \rangle + b \text{ subject to } |y_t - f(X_t)| \le \varepsilon \tag{9}$$

Finally, we applied Wavelet analysis (Wavelet Power Spectrum) to examine both the frequency and temporal localization of extreme movements:

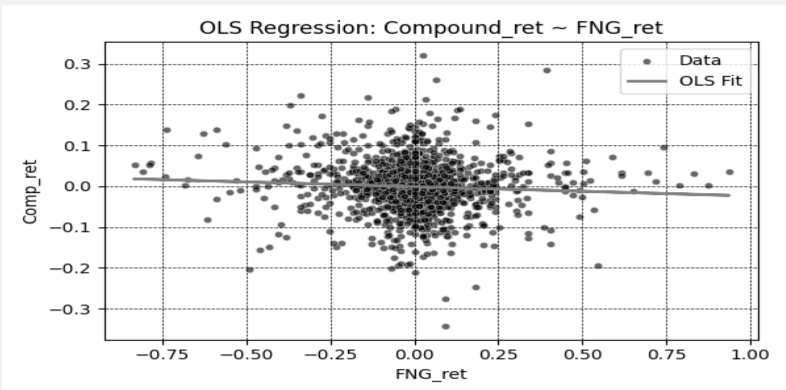
$$W_x(a,b) = \frac{1}{\sqrt{|a|}} \int_{-\infty}^{+\infty} x(t) \psi * \left(\frac{t-b}{a}\right) dt \tag{10}$$

where $W_x(a,b)$ gives the energy of the signal at a specific scale (frequency) and moment in time, helping us to identify time-localized volatility clusters and sentiment-driven bursts.

4. Interpretation of Statistical Significance

The initial stage of the empirical analysis, focused on assessing linear relationships, revealed no meaningful correlation between daily log returns of DeFi governance tokens and changes in the F&G Index. Correlation coefficients ranged from (-0.0058) to 0.078 - well below the threshold of statistical significance. Only AAVE (0.078) and UNI (0.067) showed weak positive correlations, possibly due to their greater sensitivity to short-term sentiment or structural differences in liquidity. Cross-correlation analysis confirmed the absence of lagged effects, with weak and unstable correlations that quickly diminished after lag zero across all tokens (e.g., BAL: -0.04 to +0.06; COMP: -0.06 to +0.06; UNI: -0.09 to +0.08), indicating no sustained short-term influence from the index. Given that correlation does not quantify effect size or direction, we applied OLS regression to estimate how returns respond to changes in sentiment. Regression coefficients across tokens averaged around 0.06, implying that a 1% change in FNG_ret corresponds to just a 0.06% change in token returns. However, the explanatory power of the models was extremely low: R^2 values ranged from 0.000034 (Maker) to 0.0060 (AAVE and PancakeSwap), indicating that the index explains less than 1% of return variance. Statistically significant coefficients were found for AAVE ($\beta = 0.0573$, $p < 0.001$), COMP ($\beta = -0.0228$, $p = 0.011$), and PAN ($\beta = 0.0573$, $p < 0.001$), though the effect size remained weak. For other tokens (BAL, UNI, MAKER) coefficients were not significant ($p > 0.05$), and none of the models demonstrated predictive adequacy based on R^2, RMSE, or MAE metrics. In summary, both correlation and OLS regression show that sentiment, as measured by the FNG index, has little to no explanatory or predictive power over the daily returns of governance tokens. These findings highlight the need for nonlinear and regime-sensitive modeling approaches to capture more complex dynamics (Fig. 1)

Fig. 1. OLS shows that the sentiment index does not explain return variation (R^2=0.004). with the flat regression line and dispersed data points supporting the null hypothesis of no statistically significant linear relationship between the two variables. Source: Figure created by the authors using Python



Granger causality tests were applied to assess whether changes in the FNG Index precede and help predict governance token returns. Using a 1–10 day lag structure, results for all tokens (Aave, PancakeSwap, BAL, UNI, COMP, and Maker) showed p-values above the 0.05

Vol. 1, no. 1, May 2025

threshold across all lags, indicating no evidence of Granger causality. Thus, past values of the sentiment index do not provide additional predictive information, and FNG_ret cannot be considered a leading indicator for token returns. Following the inconclusive results from OLS and Granger tests, the analysis advanced to more sophisticated models - ARIMAX, GJR-GARCH, and Markov Switching - to explore potential nonlinear and regime-dependent effects. While FNG_ret showed no predictive value in linear models, GJR-GARCH results suggest a marginal improvement in volatility forecasts during extreme sentiment phases (e.g., high fear or greed), though without statistical significance. Overall, the index does not appear to drive token price behavior but may still offer supplementary insights for risk management under specific market conditions when more sensitive models are employed.

Table 1. Results from GARCH and GJR-GARCH models

Token	GARCH -RMSE	GARCH-MAE	GARCH-R^2	GJR-RMSE	GJR-MAE	GJR-R^2
Aave	0.14931	0.089291	-0.49062	0.138704	0.08244	-0.2863
BAL	0.033928	0.027315	-0.09699	0.033929	0.02733	-0.0970
COMP	0.042787	0.03433	-0.0576	0.042876	0.034393	-0.0620
MAKER	0.051807	0.037046	-0.1965	0.051784	0.036912	-0.1954
RAN	0.037299	0.02861	-0.12325	0.0373	0.028612	-0.1233
UNI	0.2454	0.1149	-0.05552	0.2666	0.0975	-0.8356

Source: Table constructed by the author based on processed data

Although the GARCH and GJR-GARCH models produced low RMSE values (below 0.15 for most tokens), their negative R^2 scores indicate poor explanatory power regarding return volatility (Table 1). This supports the theoretical view that negative shocks (fear) have a stronger impact on volatility than positive ones (greed). The weakest performance was observed for UNI, with R^2 values of -0.5552 (GARCH) and -0.8356 (GJR-GARCH), underscoring the models' inability to capture volatility dynamics effectively. While GJR-GARCH slightly outperformed GARCH in RMSE and MAE due to its asymmetric structure, the improvements were minimal and insufficient for reliable forecasting. Using GJR-GARCH, we aimed to assess whether accounting for asymmetric effects would enhance volatility modeling in DeFi. The results showed a clear divergence: GJR-GARCH consistently forecasted higher volatility than GARCH, with a widening gap over the 20-day horizon, suggesting greater sensitivity to downside risks. This aligns with behavioral finance theory, which posits stronger market reactions to negative news. To further evaluate the role of sentiment, we applied ARIMAX models. These achieved high R^2 values (0.9877–0.9888), indicating strong autocorrelation in token prices. However, the FNG Index contributed little to prediction accuracy; in most cases, its influence was flat, resulting in nearly horizontal forecasts and wide confidence intervals - especially for PancakeSwap, BAL, and UNI. While ARIMAX captured long-term trends (e.g., BAL's decline, Fig. 2), it failed to reflect sentiment-driven dynamics. Similar results were observed for Compound and Maker, confirming that sentiment does not enhance forecast precision in this context.

Vol. 1, no. 1, May 2025

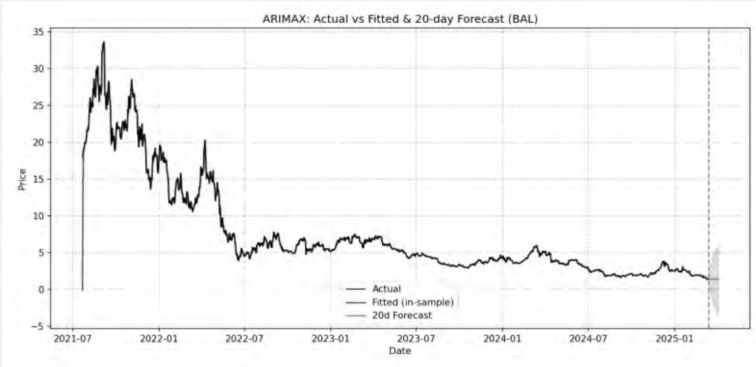


Fig. 2. ARIMAX model for BAL – long-term downward trend and flat 20-day forecast. The wide confidence interval and the absence of a directional trend in the forecast highlight the weak predictive value of the sentiment index. Sources: Figure created by the authors using Python

As shown in Fig. 2, the flat red forecast line reflects the ARIMAX model's assumption of a constant FNG value, limiting the exogenous variable's contribution. The model essentially *memorizes* the last index value, resulting in minimal forecast volatility. While FNG_ret does not directly affect returns, it influences return volatility - particularly during extreme sentiment phases - a pattern better captured by GJR-GARCH than by linear models. To examine whether sentiment affects volatility regimes rather than returns, we applied a Markov switching model, which differentiates between stable (Regime 0) and volatile (Regime 1) periods. Most tokens remained in the stable regime over 90% of the time, with brief transitions during price shocks or sentiment drops. However, FNG_ret was not a significant driver of regime shifts. Even so, detecting such shifts is valuable for risk management, as they indicate heightened uncertainty when reducing exposure or increasing hedging may be prudent.

Table 2. Interpretation of the results from Markov Regime Switching models

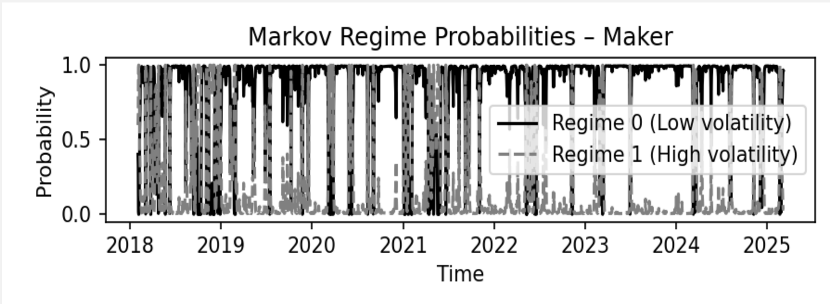
Token	Regime	FNG influence	Interpretation
Aave	Stable regime, high persistence	Not significant	Market regime is stable; FNG does not alter transitions
BAL	2 regimes	Weak effect in high volatility	Minor role of index, limited to volatile conditions
COMP	Frequent regime shifts	Potential impact	Index might influence shifts in market dynamics
MAKER	Structured regime switching	Not significant	Clear regime structure; index not relevant to switching
PAN	Strong regime-switching behavior	Index matters in stress periods	FNG index plays a role when the market is under tension
UNI	Moderate transitions	Weak influence	FNG effect is minimal, though model detects transitions

Source: Table constructed by the authors based on processed data.

Vol. 1, no. 1, May 2025

As shown in Table 2, Aave and Maker display stable regimes with no significant influence from the Fear and Greed Index, indicating relative independence from sentiment. In contrast, PancakeSwap (and to a lesser extent BAL and Compound) show moderate sensitivity to sentiment, particularly during stressed conditions marked by more frequent regime shifts. While sentiment has limited impact under normal conditions, it may affect market dynamics during periods of heightened volatility, especially for Compound and PancakeSwap.

Fig. 3. Markov regime-switching model for Maker - the stable regime and the volatile regime. Sources: Figure created by the authors using Python



Traditional linear models failed to capture the time-dependent structures in DeFi token behavior. Wavelet analysis, suited for non-stationary financial series, allowed for the identification of volatility spikes, their timing, scale, and intensity - insights often missed by correlation or ARIMA methods. The results show that Aave (Fig. 3), Compound, PancakeSwap, and Uniswap exhibit short- and medium-term volatility bursts, particularly during market stress. Aave peaked in late 2020; Compound and Uniswap showed recurring short-term cycles (scales 20-40); PancakeSwap had active zones during 2022-2023. In contrast, Maker and BAL displayed more stable patterns, with Maker showing no high-energy periods and BAL's energy concentrated at higher scales (80-120), indicating infrequent but longer-term fluctuations.

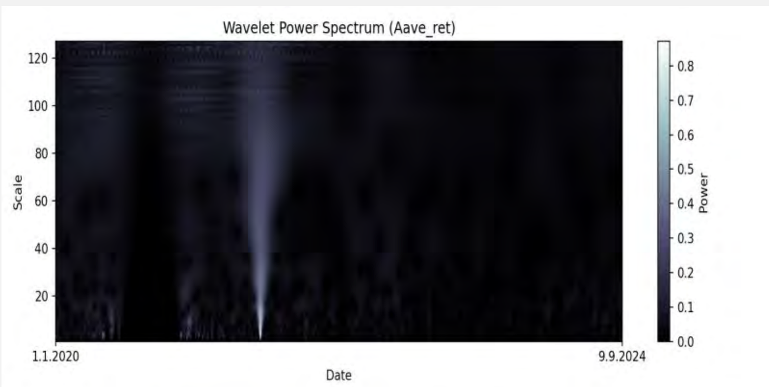


Fig. 4. Wavelet spectrum of the logarithmic returns of Aave. Source: Figure created by the authors using Python

Vol. 1, no. 1, May 2025

Fig. 4 shows a concentration of wavelet energy in late 2020 at low scales, reflecting short-term volatility during a period of DeFi sector growth. After this peak, the spectrum shifts to low-energy zones, indicating market stabilization and reduced volatility. The lack of sustained high-frequency activity suggests structural stability and limited cyclicality. To explore nonlinear dependencies between token returns and the FNG Index, we applied Support Vector Regression (SVR) and the Maximal Information Coefficient (MIC). MIC values were highest for Uniswap (0.135) and Compound (0.106), while other tokens showed minimal dependence. Since all MIC scores are below 0.2, these relationships are weak. SVR models performed poorly across tokens, with negative R^2 values, indicating that any potential nonlinear patterns are too weak to be captured (Fig. 5).

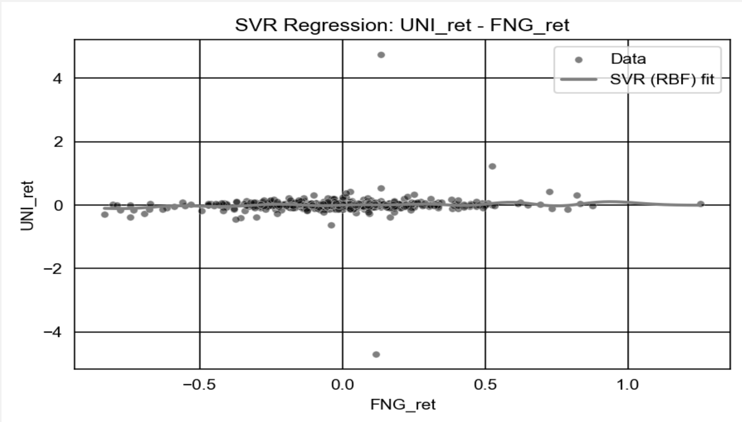


Fig. 5. Scatter plot of the daily return of UNI and changes in the F&G Index with SVR (RBF) curve. Source: Figure created by the authors using Python

Although the SVR curve suggests mild nonlinearity, it remains largely flat, confirming the weak dependence indicated by low MIC values. The impact of FNG on UNI's returns - and on other tokens, with MIC scores between 0.01 and 0.04 - is minimal. These results indicate that daily changes in the FNG Index have no significant linear, nonlinear, or predictive effect on governance token returns, supporting the need for a multi-model approach.

Conclusion

The analysis reveals a very weak relationship between daily sentiment shifts and DeFi token returns, with neither linear nor machine learning models detecting a consistent signal. This may be due to protocol-specific drivers (such as governance activity, vesting, or TVL) and the strategic behavior of long-term holders, which dilute the influence of broad market sentiment. While the Fear & Greed Index reflects systemic crypto risk, its direct effect on DeFi tokens appears limited. Any influence it may have likely occurs over longer-term price trends, regime shifts, or in conjunction with other structural market dynamics.

Author Contributions: Conceptualization - G.T.-A. and S.R.; methodology - G.T-A.; software - G.T.-A.; programming code - G.T.-A.; investigation - G.T.-A. and S.R; resources, G.T.-A. and S.R.; writing—original draft preparation, G.T.-A. and S.R.; writing—review and editing G.T.-A and S.R.

References

1. Al-Mansour, B.Y. (2020). *Cryptocurrency market: Behavioral finance perspective*. The Journal of Asian Finance, Economics and Business, 7(12), pp.159–168. doi: 10.13106/JAFEB.2020.VOL7.NO12.159.
2. Albrecht, P., Maňoušek, D. and Pastorek, D. (2023). *Riding the waves of crypto sentiment: Examining the dynamics between returns and sentiment in the cryptocurrency market*. Available at SSRN 4663473. Available at: https://ssrn.com/abstract=4663473 (Accessed: 1 May 2025).
3. Baker, M. and Wurgler, J. (2006). *Investment sentiment and the cross-section of stock returns*. The Journal of Finance, 61(4), pp.1645–1680. doi: 10.1111/j.1540-6261.2006.00885.x.
4. Barbereau, T., Smethurst, R., Papageorgiou, O., Sedlmeir, J. and Fridgen, G. (2022). *Decentralised Finance's timocratic governance: The distribution and exercise of tokenised voting rights*. Technology in Society, 73. doi: 10.2139/ssrn.4001891.
5. Bennett, D., Mekelburg, E. and Williams, T.H. (2023). *BeFi meets DeFi: A behavioral finance approach to decentralized finance asset pricing*. Research in International Business and Finance, 65(C). doi: 10.1016/j.ribaf.2023.101939.
6. Bhambhwani, S. (2025). *Governing decentralized finance (DeFi)*. SSRN. doi: 10.2139/ssrn.4513325.
7. Bouri, E., Gupta, R. and Roubaud, D. (2019). *Herding behaviour in cryptocurrencies*. Finance Research Letters, 29, pp.216–221. doi: 10.1016/j.frl.2018.07.008.
8. Campbell, R.H., Ramachandran, A. and Santoro, J. (2021). *DeFi and the future of finance*. Available at: https://ssrn.com/abstract=3711777, (Accessed: 1 May 2025).
9. da Gama Silva, P.V.J., Klotzle, M.C., Pinto, A.C.F. and Gomes, L.L. (2019). *Herding behavior and contagion in the cryptocurrency market*. Journal of Behavioral and Experimental Finance, 22, pp.1–9. doi: 10.1016/j.jbef.2019.01.006.
10. Erya, J., Qin, B., Wang, Q., Wang, Z., Wu, Q., Weng, J., Li, X., Wang, C. and Zhang, Y. (2023). *Decentralized finance (DeFi): A survey. Cryptology ePrint Archive*, Paper 2023/1210. Available at: https://eprint.iacr.org/2023/1210 (Accessed: 1 May 2025).
11. Gusev, A.A. (2018). *Public opinions impacts on cryptocurrency valuation: A view from behavioral finance perspective*. Journal of Reviews on Global Economics, 7, pp.610–619. doi: 10.6000/1929-7092.2018.07.63.
12. Harvey, C.R., Ramachandran, A. and Santoro, J. (2021). *DeFi and the future of finance*. Available at: https://ssrn.com/abstract=3711777 (Accessed: 1 May 2025).
13. Liu, Y. and Tsyvinski, A. (2021). *Risks and returns of cryptocurrency*. The Review of Financial Studies, 34(6), pp.2689–2727. doi: 10.1093/rfs/hhaa113.

Vol. 1, no. 1, May 2025

14. Poyser, O. (2018). *Herding behavior in cryptocurrency markets*. Working Paper. doi: 10.48550/arXiv.1806.11348.
15. Radu, C.-G. and Deak, E.R. (2024). *Consumer behavior in the world of cryptocurrencies*. Proceedings of the International Conference on Business Excellence, Sciendo. doi: 10.2478/picbe-2024-0026.
16. Schär, F. (2021). *Decentralized finance: On blockchain- and smart contract-based financial markets*. Federal Reserve Bank of St. Louis Review, 103(2), pp.153–174. doi: 10. 20955/r.103.153-74.
17. Shu, H.C. and Chang, J.H. (2015). *Investor sentiment and financial market volatility*. Journal of Behavioral Finance, 16(3), pp.206–219. doi:10.1080/15427560.2015.1064930.