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Choosing Solitude in Turmoil, Herding in the Decentralized Finance (DeFi) Token Market: An International Perspective

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Abstract

Financial markets have long been known to be prone to behavioral biases. One such behavioural bias that is consequential yet pervasive in financial markets is the herd effect. The objective of this study is to determine whether or not there exist herd behaviour in the new and bourgeoning Decentralized Finance (DeFi) Tokens market. This is accomplished by using daily returns of 22 DeFi tokens from January 29, 2017 to August 19, 2021, and the Cross-sectional Absolute Deviation (CSAD) of market returns to capture herd behavior. The results fail to provide any evidence of herding in the DeFi token market on bullish days, that is days for which the average market returns is positive. For bearish days however, that is days for which the market returns is negative, our empirical findings point to the presence of adverse herding in the DeFi token market. This phenomenon can be explained to some extent by the investor composition of the DeFi market. The DeFi token space is a growth market dominated by experts and/or enthusiasts who are insulated against the temptation and panic of negative market swings by the level of market and technical information they possess on the assets they invest.

Keywords: Crypto Currency, DeFi Token Market, Herding, Behavioral Economics, Behavioral Finance

JEL Classification Code: G40, G41, N20

1. Introduction

Bitcoin, the first cryptocurrency, was created to usher in a transaction system independent of third-party trust (Kayal & Rohilla, 2021) using blockchain technology. Beyond the thousands of alternative cryptocurrencies (altcoins) that have since been created using blockchain, the technology has also been used for different purposes in Finance and other industries like marketing (Calzadilla et al., 2021) and health (Zhang et al., 2018).

Even within the cryptocurrency space, there is immense variation in the purpose and functioning of cryptocurrencies. Whereas traditional cryptocurrencies like Bitcoin are primarily for exchange and store of value, stable coins serve as a vehicle to trade traditional cryptocurrencies and, to a lesser extent to act as a haven against negative price changes in conventional cryptocurrencies (Griffin & Shams, 2020). Yet another type of cryptocurrency that Corbet et al. (2021) contend constitutes a separate asset class from conventional cryptocurrencies is Decentralized Finance (DeFi) tokens. DeFi tokens are cryptocurrencies that power Decentralized Finance platforms, which have attracted attention in recent years (Ozcan, 2021).

Decentralized Finance is a collection of blockchain-powered applications that carry out traditional financial transactions as well as provide opportunities for new and innovative transactions not possible in the centralized, traditional finance setting (Ozcan, 2021). This is done by building an open, permissionless, and highly interoperable protocol stack on a public smart contract platform like the

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Ethereum blockchain (Schär, 2021). Ozcan (2021) stresses the distinction between open Finance and DeFi, noting that open Finance implies running traditional Finance on the blockchain with the associated licensing and legal requirements, whereas DeFi requires no or minimal licensing, concluding that DeFi provides more opportunities and is a broader term than open Finance. Indeed, DeFi tokens constituting a different asset class is not surprising. For one, unlike Bitcoin and altcoins, which so far offer only potential capital gain to investors, investment in DeFi tokens offers added benefits to investors beyond the capital gain in the form of interest on deposits, borrowing, and lending, ability to take short positions, and taking insurance against risks among others. This is a critical difference, which can lead to different investor behavior from the traditional cryptocurrency space.

DeFi platforms vary greatly with some platforms having a native token while others do not. When a DeFi platform does have a native token, it acts like a stock that enables holders to participate in the governance of the platform, with the platform acting as a Decentralized Financial company, producing yields and revenues (Corbet et al., 2021). This financial architecture is touted as maturing with the potential to outpace traditional central financial architecture in the years to come (Eikmanns et al., 2021). Yet little is known about the DeFi tokens, which power these platforms in the academic research space.

This study contributes to the understanding of DeFi tokens by exploring their investors' herd behavior. This is the first attempt at exploring the behavioral biases in general and the herd behavior in particular in the DeFi token space. Since it is an established consensus that herding intensifies the volatility of asset returns (Demirer & Kutan, 2006) with implications for portfolio diversification, knowledge of whether there is herding in the DeFi space will allow investors to choose the appropriate number of assets to achieve optimal diversification in their portfolios. Herding is also found to have implications for the investment strategy, with momentum strategies in the high herding loser industries found to consistently outperform low herding loser industries (Demirer & Zhang, 2019).

The objective of this study is to determine the existence or otherwise of herd behavior in the DeFi token space. Determining whether there is herding in the DeFi token space is important because of the implications of herding on investment returns and diversification. The study is accomplished using the Cross-Sectional Absolute Deviation (CSAD) of Returns to capture herding as in Chang et al. (2000), Jabeen et al. (2021), and Bharti and Kumar (2020). Three (3) models are estimated, one each for bullish days (days of positive market returns) and bearish days (days of negative market returns) and a combined result of the DeFi token market without regard for the direction of the market. The results indicate the non-existence of herding during bullish days and the existence of adverse herding on bearish days and an overall adverse herding in the DeFi token market.

The remaining of the study is structured as follows. Section 2 briefly discusses the behavioral finance and herding literature, Section 3 explains in detail the methodology employed in this study. Section 4 discusses the data. Section 5 reports and discusses the results, and Section 6 concludes the study.

2. Literature Review

Before the advent of the rational expectations theory and its derivative the Efficient Market Hypothesis (EMH), social, emotional, and psychological ideas formed the basis of many influential analyses in economics (Baddeley, 2010). Nonetheless, the rational expectations theory and the EMH came to dominate the academic discourse of financial markets at least until the 1990s. In the 1990s, attention shifted towards the development of models of human psychology as it relates to financial markets (Shiller, 2003) due to the many empirical shortcomings and/or failures found by researchers on the assertions of the EMH. For instance, the weak-form EMH conjectures that historical data have been incorporated into current market prices and that makes it impossible for investors to use historical data to outperform the market (Leković, 2018). However, Emenike and Kirabo (2018), Maasdorp (2015), and Poshakwale (1996) have all found evidence that contradicts weak-form market efficiency.

The semi-strong form EMH contends that investors cannot outperform the market using the knowledge that is available to all other investors, like company earnings, since information is rapidly (almost instantaneously) incorporated into market fundamentals. Ball (1978) however found that stock prices adjust slowly to earnings information making it possible for investors to make buy decisions after receiving news on company earnings and still cash in. These have led to (or perhaps caused the return to) behavioral finance which contends that the decisions of ordinary investors are in part influenced by their psychological, sociological, and emotional preparations and investors' personal biases (Calzadilla et al., 2021). Institutional investors who are generally thought of as being savvier and more rational have also been found to be susceptible to these biases by Gunathilaka and Fernando (2021).

One of the behavioural biases widely documented in financial markets is herd behavior. According to Devenow and Welch (1996), herding is a basic human instinct, which can be said to be rational or non-rational. They explain rational herding as arising due to three effects. The first is the payoff externalities, which occurs when the payoff to an agent taking a course of action is an increasing function of the number of other agents taking that same course of action.

The second is the principal-agent problem, which occurs when imperfect information causes agents to try to gain or preserve reputation by following the herd. The third is information cascades, which result from when later agents optimally decide to ignore their own beliefs due to the actions of prior agents. The non-rational herding is construed as market participants ignoring their private beliefs to follow other market participants blindly. Herding especially the non-rational type is not always benign with Persaud (2000) contending that in the presence of herding, tight market-sensitive risk management systems and more transparency make markets less stable and more prone to crisis and as such can be instrumental in explaining bubbles and bursts (Avery & Zemsky, 1998). Herding has also been found to increase volatility in stock markets (Blasco et al., 2012; Chen et al., 2018), and affect the risk-return trade-off, and asset pricing (Gębka & Wohar, 2013). Investing in markets prone to herding requires a larger number of securities to achieve the same level of portfolio diversification as compared to a market less prone to herding (Chang et al., 2000).

Despite the negative repercussions of herd behavior, it is found to exist in stock markets (Chang et al., 2000; Christie & Huang, 1995; Luu & Luong, 2020; Simões Vieira & Pereira, 2015; Wermers, 1999) forex markets (Sherman, 2011), commodities market (& Mokni, 2020) and the bourgeoning cryptocurrency market (Bouri et al., 2019; da Gama Silva et al., 2019; Jalal et al., 2020; Omane-Adjepong et al., 2021; Papadamou et al., 2021).

With the divergence in purpose and functioning of cryptocurrencies (Corbet, et, al, 2021), DeFi investor behavior could likely differ from the behavior of traditional cryptocurrency and/or stable currency traders. This study seeks to determine the herd behavior in the DeFi market.

3. Methodology

Christie and Huang (1995) were the first to propose a market-based measure of herding. They argued that rational asset pricing models predict that the Cross-Sectional Standard Deviation (CSSD) will increase with the absolute value of the market return since individual assets differ in their sensitivity to the market return. In the presence of herding, however, asset returns will not deviate too far from the overall market return resulting in an increasing dispersion at a decreasing rate or even a decrease in dispersion in the case of severe herding. This will result in a dispersion that contradicts the prediction of the Capital Asset Pricing Model (CAPM) (Chang et al., 2000). For this, they suggest the use of CSSD to be regressed on the market returns as in equation 1 to capture herd behavior in financial markets.

$$\text{CSSD}_t = \alpha + \beta^L D_t^L + \beta^U D_t^U + \varepsilon_t \tag{1}$$

With $D^L{}_t$ and $D^U{}_t$ being dummy variables that capture extreme market returns in the lower and upper tails respectively. A negative and significant β_i will then be seen as evidence for the presence of herding (Christie & Huang, 1995). Chang et al. (2000) contend that this methodology will require a much greater magnitude of non-linearity far greater than the Capital Asset Pricing Model (CAPM) suggests. In response, they proposed the use of the Cross-Sectional Absolute Deviation (CSAD) which is derived from Black's (1972) version of the Capital Asset Pricing Model (CAPM). Black's (1972) version of CAPM predicts that the expected return of an asset *i* is equal to the return on a risk-free asset like government bonds and a risk premium. This is captured as in equation 2.

$$E\left(R_i\right) = R_f + \beta_i (E\left(R_m - R_f\right) \tag{2}$$

Where R_f are the zero–beta (risk-free asset) returns, β_i is the time-invariant systematic risk of the asset and R_m is the return on equally weighted portfolio returns. Per this, the portfolio beta can be estimated as the simple mean of the *n*-asset _betas as in equation 3.

$$\beta_m = 1/n\sum_{i=1}^{n}\beta_i \tag{3}$$

With β_m being the portfolio beta. From this, they obtain the Absolute Value of Deviation (AVD_{it}) of returns of asset *i* at time *t* as

$$AVD_{it} = \left|\beta_i - \beta_m\right| E\left(R_m - R_f\right) \tag{4}$$

And the expected cross-sectional absolute deviation (ECSAD) of returns of the portfolio as

$$\text{ECSAD}_t = \frac{1}{N}\sum_{i=1}^{N}\text{AVD}_{it} = \frac{1}{N}\sum_{i=1}^{N}\left|\beta_i - \beta_m\right| E\left(R_m - R_f\right) \tag{5}$$

Taking the first difference of this with respect to the market returns R_m will result in

$$\frac{\partial E\text{CSAD}_t}{\partial E\left(R_m\right)} = \frac{1}{N}\sum_{i=1}^{N}\left|\beta_i - \beta_m\right| > 0 \tag{6}$$

And the second derivative with respect to market returns R_m will be zero (0).

$$\frac{\partial^2 E\text{CSAD}_t}{\partial E(R_m)^2} = 0 \tag{7}$$

This then proves that, per the CAPM, there is a strictly linear relationship between ECSAD, and the market returns, and any deviation from this could mean investors are herding around the market consensus (Chang et al., 2000). To apply this methodology, however, we need a proxy for the ECSAD_t since it is not directly observable (Chang et al., 2000). The CSAD_t estimated as in equation 8 accomplishes this.

$$\text{CSAD}_t = \frac{1}{N}\sum_{i=1}^{N} | R_{it} - R_{mt} | \tag{8}$$

Knowing that the relationship between the CSAD and the market returns is supposed to be linear, any higher order derivative beyond the first will be 0. A quadratic term of the market returns can be regressed on CSAD as in equation 9 to capture the non-linearity.

$$\text{CSAD}_t = \alpha + \gamma_1 \left| R_{mt} \right| + \gamma_2 R_{mt}^2 \tag{9}$$

If the quadratic non-linear term is statistically insignificant, then the hypothesis of the CAPM is not violated. However, a significant quadratic term will serve as proof of non-linearity and a deviation from the CAPM hypothesis.

To allow for the possibility of asymmetric herding behavior on bullish days and bearish days, Chang et al. (2000) proposed the estimation of two regressions. One for the bullish days (up days), that is, days for which the market returns are positive, and the bearish days (down days), that is, days for which the market returns are negative as in equations 10a and 10b.

$$\text{CSAD}_t = \alpha + \gamma_1^{UP} \left| R_{mt}^{UP} \right| + \gamma_2^{UP} (R_{mt}^{UP})^2 \tag{10a}$$

$$\text{CSAD}_t = \alpha + \gamma_1^{Down} \left| R_{mt}^{Down} \right| + \gamma_2^{Down} (R_{mt}^{Down})^2 \tag{10b}$$

The absolute of the linear term is meant purposely to aid in the comparison of the magnitudes. Per these equations, a negative and statistically significant γ_2 will be indicative of herding which means that investors are prone to ignoring their private beliefs and instead follow the market consensus. A positive and statistically significant γ_2 however, will be indicative of adverse herding which results when there is a higher market dispersion than the rational CAPM model predicts. Under adverse herding, investors largely ignore information conveyed by market-wide price movement and focus on views dominant among a subset of actors in a way that is excessive and exaggerated (Gębka & Wohar, 2013).

The current study follows this methodology to explore the herd behavior in the DeFi token market. We use the daily market prices of the tokens to obtain token returns. These token returns are averaged as in equation 11 to obtain daily market returns.

$$R_{mt} = \frac{1}{N}\sum_{i=1}^{N} R_{it} \tag{11}$$

Where R_{mt} is the market returns at time t, R_{it} is the returns on token i at time t and N is the number of tokens with price data on day t. The market returns, R_{mt} is then used to estimate the CSAD_t as in equation 8. Having computed the market returns, R_{mt}, and the CSAD_t, we estimate regression 9 and regressions 10 to determine if there is herding in the DeFi token market on the bullish days (Up) and the bearish days (Down) using ordinary least squares with Newey and West's (1987) standard errors as in Chang et al. (2000).

4. Data

The DeFi market is an increasing space with over 400 protocols currently running. These protocols may or may not have a native token attached to the platform (Corbet et al., 2021). Our study is limited to only DeFi protocols with native tokens and with price data available on Yahoo! Finance[1]. Using this criterion, daily closing price data of 22 DeFi tokens[2] from 29-01-2017 to 19-08-2021 is used in this study. The returns of each DeFi token are obtained by taking the log difference of the closing prices. The descriptive statistics for the token returns are given in Table 1.

The highest number of observations is the GNOSIS (GNO) with 1564 observations. Gnosis is a protocol for the prediction market and employs a dual token structure with Gnosis (GNO) staked to generate owl tokens. To do this, a GNO token holder must lock their tokens into a smart contract, which prevents them from transferring and/or trading their tokens for a specified duration. A smart contract is a computer-embedded contractual clause with self-execution capacity without the need for a trusted intermediary (Ozcan, 2021). The number of owl tokens that are generated based on the locked GNO depends on the duration and the number of owl tokens in the market (Gnosis, 2017).

The token with the lowest number of observations is the Graph with only 140 data points. The Graph is a protocol for organizing blockchain data and serving as the 'google' of the blockchain. Per the Graph's[3] website, indexers in the Graph network stake the Graph (GRT2) tokens to provide indexing and query processing services for which they earn query fees and indexer rewards for their services. These 22 tokens make up over 70% of the market capitalization of all DeFi tokens of which Aave is the dominant token with a 15.33%[4] dominance index as of 19/08/2021 according to https://DeFipulse.com. By using the token returns, we compute equally weighted market portfolio returns as stipulated in equation 11.

To ensure that there is a non-zero , we limit ourselves to days for which we have at least 2 tokens' data. With this, the descriptive statistic for the market returns and the Cross-Sectional Absolute Deviation, is presented in Table 2.

As seen in Table 2, the market returns for the whole sample, is negatively skewed implying more extreme

Table 1: Descriptive Statistics of DeFi Token Returns

Tokens	Obs	Mean	S. D	Skewness	Kurtosis
Aave	157	–0.002276	0.083904	–0.745366	6.380370
Ach	322	0/.005937	0.146434	2.592680	17.78591
Ankr	708	–0.000880	0.075242	–0.691952	12.6644
Avax	322	0.005459	0.091948	0.545466	10.04410
BNT	1516	–0.001183	0.077134	–5.516852	115.7772
Comp	241	0.001856	0.102906	2.085568	21.27037
CRV	185	–0.007178	0.110276	–0.629980	7.348861
GNO	1564	0.000382	0.069522	0.108741	9.243414
GRT2	140	–0.004788	0.086538	–1.083727	9.439093
KAVA	474	0.000300	0.083349	–1.883239	19.27058
KNC	1418	–6.87E–05	0.073344	–0.268860	9.107781
LINK	1422	0.003314	0.078285	0.021715	9.407236
LRC	1443	0.000625	0.087351	–0.537771	14.41387
LUNA1	667	0.005154	0.083438	0.88156	14.00745
MKR	1221	0.000782	0.067549	–0.819533	26.04628
RSR	463	0.002172	0.082460	–0.691134	12.05532
RUNE	463	0.007000	0.097964	–0.340435	4.641774
SNX	1087	0.001154	0.086536	0.115989	7.569089
SUSHI	173	0.001527	0.148692	1.361935	20.14526
UMA	263	0.003886	0.090180	0.160264	6.735913
UNI3	167	–0.000440	0.080982	–0.342396	8.950073
YFI	207	0.013896	0.116798	1.005555	7.457438

Table 2: Descriptive Statistics for CSAD and Market Returns

	Obs	Mean	S.D	Skewness	Kurtosis
CSAD	1516	0.037856	0.029761	10.94657	245.6100
R^m	1516	0.000379	0.062432	–2.431759	26.89294
$CSAD^{up}$	843	4.087e-02	0.0245054	1.809928	7.749122
R^m_{up}	843	3.826e-02	0.03365908	1.597617	6.669791
$CSAD^{down}$	673	0.034097	0.03490902	14.67773	296.3572
R^m_{down}	673	–0.0470034	0.05764939	–5.538045	57.36512

negative values than extreme positive values (Chiang & Li, 2015) in the DeFi token market returns. Also, both the CSAD and the are leptokurtic which is a regular occurrence in financial markets (Dhesi et al., 2021) to the extent that the fat tails are almost considered a stylized fact.

The skewness and kurtosis for the bullish days (Up) are much lower than those for the bearish days (Down) even though both indicate an abnormality in their distribution. Figure 1 and Figure 2 depict the time series of the CSAD and the market returns (R_m).

5. Results and Discussion

The OLS regression results of equation (9), equation (10a), and equation(10b) are presented in Table 4. Results of equation (9) are reported as the full set model. The estimated

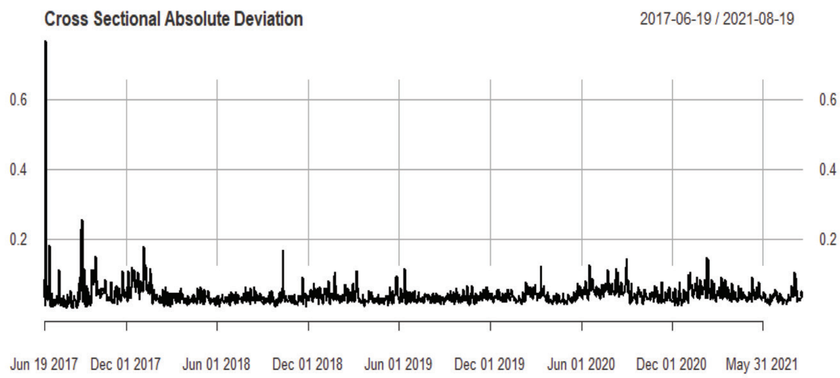

Figure 1: Cross-sectional Absolute Deviation of Market Returns

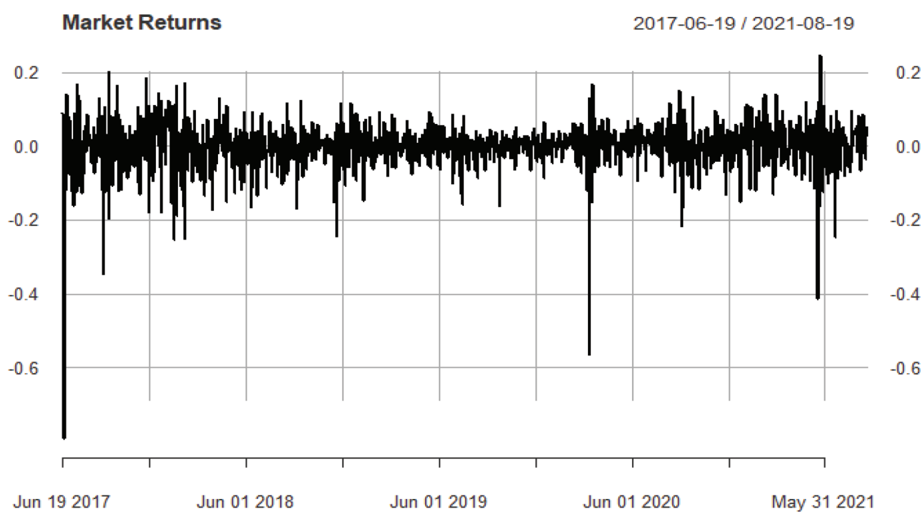

Figure 2: Market Returns

Table 3: OLS Regression Results

	Full set		Up		Down	
	Coefficient	***t*-stats**	**Coefficient**	***t*-stats**	**Coefficient**	***t*-stats**
α	0.0329	22.89***	0.0282	20.15***	0.0325	16.783 ***
γ^1	0.0351	0.653	0.3748	5.56***	0.096343	1.655
γ^2	0.8893	3.40***	–0.658483	–1.46	1.0998	4.877 ***
adj.R^2	0.4021		0.1586		0.6295	
F-stats	510.4***		80.34***		572***	

Estimation result $\text{CSAD}_t = \alpha + \gamma_1 \left|R_{mt}\right| + \gamma_2$ for the model in eqn. (9), $\text{CSAD}_t = \alpha + \gamma_1^{UP} \left|R_{mt}^{UP}\right| + \gamma_2^{UP} (R_{mt}^{UP})^2$ for the model in eqn. 10(a) and $\text{CSAD}_t = \alpha + \gamma_1^{Down} \left|R_{mt}^{Down}\right| + \gamma_2^{Down} (R_{mt}^{Down})^2$ for the model in eqn. 10(c) using OLS with Newey and West's (1987) Standard Errors. ***denotes significance at 1% level.

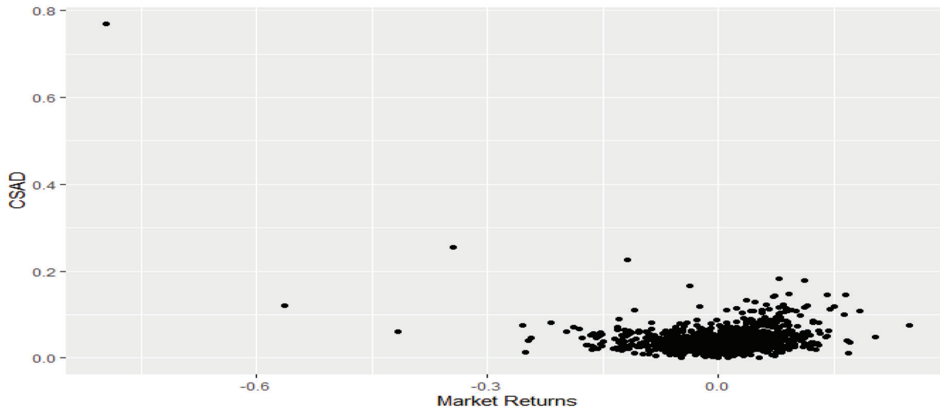

Figure 3: Relationship Between CSAD and Market Returns

results of equation (10a) which represent days for which the market returns were greater than zero (bullish days), and (10b), which represent days for which the market returns were less than zero (bearish days) are reported as the up and down models respectively.

From the full-set model, we find a positive and statistically significant intercept term of 0.0329. This implies that, in the DeFi token market, the average token return dispersions in a stagnant market with market returns equalling zero (Chang et al., 2000) is 3.29%. For the up model, the average token returns dispersion is 2.81% and 3.25% for the down model respectively. This parallels the findings of Chang et al. (2000), who found positive average return dispersion for stocks of the US, Hong-Kong, Japan, South Korea, and Taiwan, and the findings of Ballis and Drakos (2020) who arrived at a similar result in a study of 6 major traditional cryptocurrencies including Bitcoin, Dash, Ethereum, Litecoin, Monero, and Ripple.

The linear term which depicts the contribution of market returns, $|R_m|$, to the Cross-Sectional Absolute Deviation (CSAD) is positive and insignificant in the full-set model and the down model with γ_1 being 0.0351 and 0.0963, respectively. This is interesting since it contradicts the hypothesis that CSAD increase with an increase in the absolute value of the market returns as propounded by Chang et al. (2000) and confirmed by several studies in the cryptocurrency market including Ballis and Drakos (2020), Bouri et al. (2019), Vidal-Tomás et al. (2019) and most recently by Omane-Adjepong et al. (2021) and traditional financial markets by Chang et al. (2000) and Gębka, and Wohar (2013). In the up model, however, there is a strongly significant positive relationship between the CSAD and market returns $|R_m|$ with a coefficient of 0.374. This implies that CSAD increases with market returns $|R_m|$ on the days market returns are on the rise but the relationship breaks down when market returns are on the decline.

The variables of focus, γ_2, γ_2^{UP} and γ_2^{Down} which capture herding behavior in the full set, up and down models are 0.8893, –0.6584, and 1.0998, respectively, with only the full-set and the down model being significant and the up model insignificant. These imply adverse herding in full-set and down models with no evidence of herding or adverse herding in the up-model.

The results of the up model are consistent with the predictions of the rational asset pricing model with CSAD increasing linearly with market returns. This implies that during a bullish market, investors in the DeFi space do not herd.

The bearish days however, are inconsistent with the rational asset pricing model with market turmoil resulting in increasing CSAD. This is to say that market participants in the DeFi market trade away instead of around the market consensus on days the market sentiment is bearish similar to the findings of Gleason et al. (2004) and Goodfellow et al. (2009). This can be seen as a sign of overconfidence on the part of market participants, which will result in investors betting against the market. Adverse herding could also mean that investors tend to be more cautious during periods of market downturn and, as such, rely on personal information and views instead of following the dominant market sentiment (Mertzanis & Allam, 2018). Also, the DeFi market is fairly new with the majority of investors in this class of assets being experts and/or enthusiasts with a considerable level of insider technical and market information (Mertzanis & Allam, 2018) on the assets what they are investing in. This makes them resilient to the temptation and panic of market-wide swings. Another reason for adverse herding could be an excessive flight to quality (Gębka & Wohar, 2013) when investors turn to run to established DeFi platforms during periods of market downturn.

Figure 3 depicts the relationship between the market returns and CSAD and indeed the relationship does not seem linear with a wider spread on the left side of zero (0) market returns.

This further proves that contrary to the conventional cryptocurrency market for which several studies (Bouri et al., 2019; da Gama Silva et al., 2019; Gurdgiev & O'Loughlin, 2020; Jalal et al., 2020; Omane-Adjepong et al., 2021; Papadamou et al., 2021; Vidal-Tomás et al., 2019) have found evidence of herd behavior, there is no evidence in support of herding in the DeFi token market, but rather adverse herding is observed during market down-turns.

6. Conclusion

This study sought to determine if there is evidence of herd behavior in the DeFi token market. This is utterly important as investors in a market with herd behavior will require a larger number of securities (tokens) to achieve the same level of market diversification than investors in a normal market (Chang et al., 2000).

Using the non-linearity between cross-sectional absolute deviation and market returns to capture herd behavior, this study finds evidence of adverse herding in the DeFi token market. Dividing the observations into days with positive and negative market returns, we found that days with positive market returns confirm the prediction of rational asset pricing but days with negative market returns deviate from the rationality assumption with evidence of adverse herding. This could mean that the DeFi market is made up of investors with information that insulates them from non-rational herding, are confident (perhaps overconfident) in their own beliefs, or fly to quality during periods of market turmoil.

These results bring to the question of the best investment strategy in the DeFi token space given the adverse herding found during bearish days. Future research might consider the pursuance of this question worthwhile.

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Endnotes

1 https://finance.yahoo.com/

2 These tokens and their common abbreviations are: Aave (AAVE-USD), AlchemyPay USD (ACH-USD), Ankr USD (ANKR-USD), Avalanche USD (AVAX-USD), Bancor USD (BNT-USD), Compound USD (COMP-USD), CurveDAOToken USD (CRV-USD), Gnosis USD (GNO-USD), TheGraph USD (GRT2-USD), Kava USD (KAVA-USD), KyberNetwork USD (KNC-USD), Chainlink USD (LINK-USD), Loopring USD (LRC-USD), Terra USD (LUNA1-USD), Maker USD (MKR-USD), ReserveRights USD (RSR-USD), THORChain USD (RUNE-USD), SynthetixNetworkToken USD (SNX-USD), Sushi USD (SUSHI-USD), UMA USD (UMA-USD), Uniswap USD (UNI3-USD), yearnfinance USD (YFI-USD)

3 https://thegraph.com/blog/the-graph-grt-token-economics

4 https://DeFipulse.com/