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Evaluating the Significance of the Total Value Locked to Market Capitalization Ratio

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Abstract

This study investigates the impact of the total value locked to market capitalization (T/M) ratio on the returns of four major cryptocurrencies, using daily data spanning from March 2021 to June 2024. Employing a GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model, the analysis reveals a significant negative relationship between the T/M returns and the returns of the corresponding cryptocurrency. In contrast, the T/M ratio differences of peer tokens exhibit a positive relation with the returns of the analyzed cryptocurrency. These findings suggest that the T/M ratio dynamics are crucial in influencing token performance, offering new insights into the interconnected behavior of digital assets within the broader cryptocurrency market.

Keywords: DeFi, GARCH, Tokens, Total Value Locked to Market Cap Ratio, TVL

1. Introduction

This study examines the effect of the total value locked (TVL) to market capitalization (MCAP) ratio on the price of selected tokens over time, showing its significance and impact on the returns of its network and the other networks. This study shows the negative relation that this index has on the returns of its respective network, while it has a positive relation to the other tokens. The significance of this study is that we examine the ratio's characteristics in assessing the quantitative properties of the returns of the tokens.

The TVL metric is regarded as a DeFi performance and popularity indicator (Awyong, 2022; Likhitha et al., 2023). An equivalent to the book-to-market ratio could be the TVL-to-market cap ratio (Luo et al., 2024) as it shares similarities with the assets that a company holds and the market value that it has, while Bhambhwani & Huang (2024) liken TVL to bank deposits, finding similarities between the user confidence to the security of a DeFi protocol to the equivalent of a customer confidence to a bank. The book-to-market is widely used in traditional financial theory for firms' evaluation purposes, but there are differences between it and the T/M ratio. In the crypto asset (CA) domain, there is no strict definition of a "book" or "equity" that a smart contract could have. A firm's shareholders could own a firm's equity, but the shareholders could not necessarily withdraw their respective portion of the company's equity at will; it would be under the administration of the firm's legal representatives. Assuming the TVL was the equivalent of the equity that a smart contract could hold, there could be a critical difference that the assets that are held in DeFi applications, while administered by the smart contract protocols, are finally owned by the users that have given their, conditionally revokable, permission for the protocol to use their assets in accordance to the smart contract's rules.

While a high TVL would indicate that its users trust a crypto network to hold their assets, using its absolute values might not reflect its significance in the network that holds it. Therefore, it would be helpful for a researcher to make a respective comparison to the market value that this network has, making a T/M ratio helpful in assessing how much value a network holds in its applications compared to its market value, possibly indicating an overall quality index of a network. Therefore, the motivation of this study is to determine if the T/M ratio is a significant indicator in explaining token returns and if it behaves similarly to how the book-to-market ratio behaves in stock returns.

The study commences with a literature review in section 2, proceeds to the methodology in section 3, presents the results in section 4, continues with a discussion in section 5, and concludes in section 6.

2. Literature Review

Stepanova and Eriņš (2021) included TVL as an essential metric for evaluating DeFi applications and documented the TVL values of relevant DeFi applications. Grigorova et al. (2024) emphasized the significance of TVL as a metric for evaluating tokens, while Ke and Ng (2022) use TVL to gauge a protocol's value and user adoption. Maouchi et al. (2022) found that TVL is generally negatively associated with CA bubbles; However, this relationship did not hold for specifically selected tokens, noting a positive relation between TVL and the level of trust that users place in a DeFi application, indicating that TVL can be seen as a reflection of the market performance and perceived value of a DeFi platform, as higher TVL is linked to greater user confidence in the application. Şoiman et al. (2023) conducted a panel ordinary least squares regression to investigate the impact of the TVL to MCAP ratio on the returns of selected tokens, with their findings revealing a complex temporal relationship, with the two-week lagged values exhibited a positive correlation with token returns, while the three-week lagged values showed a negative association. Moro-Visconti & Cesaretti (2023) examined the ratio of MCAP to TVL for cryptocurrency projects and posited that a project with an MCAP-to-TVL ratio below unity may be classified as overvalued. However, a ratio exceeding unity suggests undervaluation, suggesting that this framework provides a quantitative approach to assessing the relative valuation of blockchain-based projects. Dahlberg and Dabaja (2021) analyzed specific cryptocurrencies, examining the relationship between their TVL and their respective market prices, with their investigation yielding heterogeneous outcomes, encompassing both positive and negative relations, with varying degrees of statistical significance observed across the resulting coefficients.

3. Methodology

3.1 Data Analysis

The analyzed networks in this study are Ethereum (ETH), Binance Smart Chain (BSC), Solana (SOL), and TRON. The analyzed data in this study regarding TVL was collected by DefiLlama (n.d.), and the prices of the examined networks' native tokens are from Coingecko (n.d.) for the period from March 18, 2021, to June 16, 2024, denoted in United States Dollars (USD).

In Formula (1), we present how TVL is calculated.

$$TVL_{k,t} = \sum_{k=1}^{n} TS_{k,t} \cdot P_{k,t} \tag{1}$$

In Formula (1), *TVL* is the total value locked, *TS* is the token supply of locked crypto-asset tokens, *P* is the reported exchange price of the CA *k* in USD for n number of assets, and *t* is the period of reference.

The MCAP formula for a CA is presented in Formula (2).

$$MCAP_{k,t} = CS_{k,t} \cdot P_{k,t} \tag{2}$$

Where *CS* is the circulating supply of the CA *k* at period *t*.

Therefore, the T/M ratio is calculated using Formula (3).

$$T/M_{k,t} = \frac{TVL_{k,t}}{MCAP_{k,t}} \tag{3}$$

In Formula (3), *T/M* is the ratio of *TVL* to *MCAP*, showing the ratio of the value of the underlying assets on the examined token to its MCAP.

The analyzed variables in this study are presented in Table 1 and their meanings.

Table 1. Examined variables

Variable	Variable Meaning
r_ETH	Ethereum native token price
r_BNB	Binance Smart Chain native token price
r_SOL	Solana native token price
r_TRX	Tron native token price
r_BTC	Bitcoin price
d_ETH_TM	ETH TVL to MCAP ratio
d_BSC_TM	BSC TVL to MCAP ratio
d_SOL_TM	SOL TVL to MCAP ratio
d_TRON_TM	TRON TVL to MCAP ratio

Note. The prefixes "r" and "d" denote the natural log returns and natural log differences of the prices and ratios, respectively.

The analyzed variables underwent natural log differencing to achieve stationarity, as they were identified as I(1) processes at their levels; consequently, the variables are represented based on their returns and differences. Table 2 presents the results of the stationarity tests performed on the examined variables at their natural log differences.

Table 2. Stationarity tests

ADF Test	Variable								
	r_ETH	r_BNB	r_SOL	r_TRX	r_BTC	d_ETH_TM	d_BSC_TM	d_SOL_TM	d_TRON_TM
With Constant	-(36.26)	-(37.36)	-(35.29)	-(39.12)	-(35.60)	-(43.68)	-(46.01)	-(13.17)	-(46.34)
	.00***	.00***	.00***	.00***	.00***	.00***	.00***	.00***	.00***
With Constant &	-(36.25)	-(37.35)	-(35.28)	-(39.11)	-(35.69)	-(43.66)	-(46.10)	-(13.20)	-(46.33)
Trend	.00***	.00***	.00***	.00***	.00***	.00***	.00***	.00***	.00***
With no Constant &	-(36.27)	-(37.36)	-(35.27)	-(39.13)	-(35.61)	-(43.69)	-(46.02)	-(13.17)	-(46.35)
Trend	.00***	.00***	.00***	.00***	.00***	.00***	.00***	.00***	.00***

Note. The values in parentheses "() "denote the t-statistics of the test. The asterisks "***" denote significance at the 1% level.

3.2 The GARCH Model

In this study, we investigate the impact of a set of exogenous variables on the dependent variable. However, upon detecting ARCH effects in the residuals, we transition to a GARCH(1,1) model proposed by Bollerslev (1986) to capture the conditional heteroscedasticity in the data. The examined dependent variables will be *r_ETH*, *r_BNB*, *r_SOL*, and *r_TRX*, for which we possess the T/M ratio data. The remaining variables will be incorporated into the conditional mean equation to assess their potential influence on the dependent variables. The conditional mean models that this study will examine are presented in equations (4) to (7).

$$r_{ETH,t} = c + \xi_1 r_{BNB,t} + \xi_2 r_{SOL,t} + \xi_3 r_{TRX,t} + \xi_4 r_{BTC,t} + \xi_5 d_{ETH_{TM},t} + \xi_6 d_{BSC_{TM},t} + \xi_7 d_{SOL_{TM},t} + \xi_8 d_{TRON\_TM,t} + \varepsilon_t \tag{4}$$

$$r_{BNB,t} = c + \xi_1 r_{ETH,t} + \xi_2 r_{SOL,t} + \xi_3 r_{TRX,t} + \xi_4 r_{BTC,t} + \xi_5 d_{ETH_{TM},t} + \xi_6 d_{BSC_{TM},t} + \xi_7 d_{SOL_{TM},t} + \xi_8 d_{TRON\_TM,t} + \xi_9 r_{BNB,t-1} + \varepsilon_t \tag{5}$$

$$r_{SOL,t} = c + \xi_1 r_{BNB,t} + \xi_2 r_{ETH,t} + \xi_3 r_{TRX,t} + \xi_4 r_{BTC,t} + \xi_5 d_{ETH_{TM},t} + \xi_6 d_{BSC_{TM},t} + \xi_7 d_{SOL_{TM},t} + \xi_8 d_{TRON\_TM,t} + \xi_9 r_{SOL,t-1} + \varepsilon_t \tag{6}$$

$$r_{TRX,t} = c + \xi_1 r_{BNB,t} + \xi_2 r_{SOL,t} + \xi_3 r_{ETH,t} + \xi_4 r_{BTC,t} + \xi_5 d_{ETH_{TM},t} + \xi_6 d_{BSC_{TM},t} + \xi_7 d_{SOL_{TM},t} + \xi_8 d_{TRON\_TM,t} + \xi_9 \sum_{i=1}^{2} r_{TRX,t-j} + \varepsilon_t \tag{7}$$

Where c is the constant and ξ is the coefficient of the respective exogenous variable in the model. The error term ε is calculated as in equation (8).

$$\varepsilon_t = e_t \sigma_t \tag{8}$$

Where e is a white noise term following the normal distribution and σ is the conditional standard deviation. The conditional variance equation is presented in equation (9).

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 \tag{9}$$

Where σ^2 is the conditional variance, ω is the constant, α is the coefficient that captures the impact of the past squared residuals, and β is the coefficient that captures the impact of the past conditional variance.

The rationale for choosing the variables in the analyzed models is twofold: first, we aim to investigate the interdependencies among the four primary tokens with the highest TVL; second, we want to assess the influence of Bitcoin, the cryptocurrency with the largest MCAP, on these tokens. Furthermore, incorporating autoregressive terms may help ensure the model is free from autocorrelation and other specification errors.

4. Results

4.1 Data Descriptives and Stationarity Tests

Figure 1 illustrates that the four networks selected for our analysis represent the largest share of the total TVL in the cryptocurrency market.

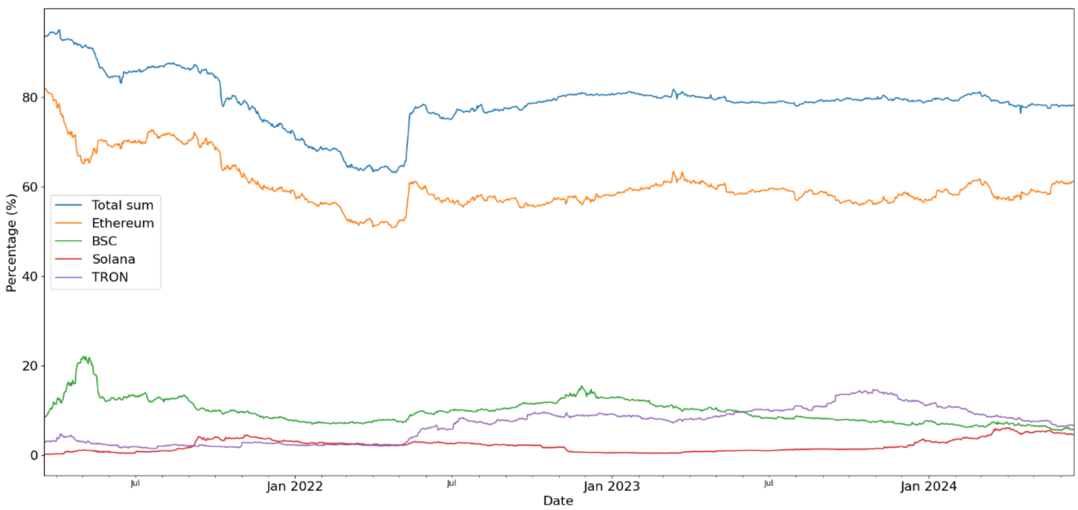

Figure 1. Share of total TVL in percentage terms

Figure 1 shows that the total TVL sum in the examined networks starts at approximately 93 percent of the overall TVL in the cryptocurrency market in March 2021. The total sum then drops to a low of around 63 percent until March 2022, when a significant increase in Ethereum's TVL raises its TVL from about 50 percent to above 60 percent. The total sum for the examined variables stabilizes at about 80 percent, maintaining this level for the remainder of the analyzed period.

In Figure 2, we observe the T/M ratios of the examined variables.

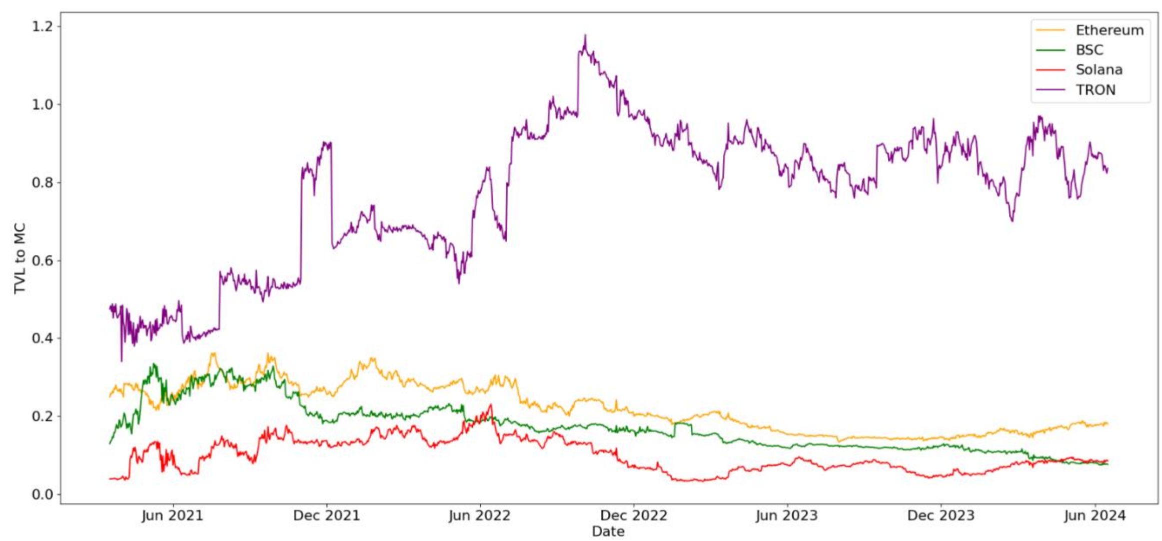

Figure 2. TVL to MCAP ratios of Selected Networks

TRON's T/M ratio starts at around 0.4 and rises to a peak of approximately 1.2 before stabilizing at roughly 0.8 for the remainder of the period. Ethereum's T/M ratio ranges between 0.2 and 0.3 for most of the sample, eventually settling at the lower end of that range around 0.2. BSC's T/M ratio begins at about 0.13, climbs to 0.3, and then gradually declines to around 0.1 by the end of the sample period. Solana's T/M ratio starts at 0.04 and increases to 0.2 in June 2022 but then trends downward, ending at approximately 0.1.

Table 3. Descriptive statistics

Statistic	Variable								
	r_ETH	r_BNB	r_SOL	r_TRX	r_BTC	d_ETH_TM	d_BSC_TM	d_SOL_TM	d_TRON_TM
Mean	.00	.00	.00	.00	.00	.00	.00	.00	.00
Standard Deviation	.04	.04	.06	.04	.03	.02	.03	.07	.04
Range	.52	.66	.83	.71	.31	.26	.42	1.28	.74
Maximum	.22	.27	.28	.33	.13	.13	.21	.71	.39
Minimum	-.31	-.38	-.55	-.38	-.17	-.13	-.22	-.57	-.35
Median	.00	.00	.00	.00	.00	.00	.00	.00	.00
Skewness	-.45	-.88	-.67	-.17	-.33	-.03	-.15	.66	1.06
Kurtosis	8.71	14.59	12.21	18.48	6.55	6.62	11.74	27.02	42.70
Jarque-Bera	1649.60	6795.28	4282.83	11846.97	646.23	646.18	3782.89	28595.44	78087.80
Jarque-Bera p-val.	.00*	.00*	.00*	.00*	.00*	.00*	.00*	.00*	.00*

Note. The asterisk (*) indicates rejection of the null hypothesis of normality at the 5% significance level. The variables have 1,187 observations.

Table 3 presents the descriptive statistics for the variables *r_ETH*, *r_BNB*, *r_SOL*, *r_TRX*, *r_BTC*, *d_ETH_TM*, *d_BSC_TM*, *d_SOL_TM*, and *d_TRON_TM*. All variables have a zero mean, indicating a balanced distribution around the mean. The standard deviations range from 0.02 to 0.07, suggesting varying levels of dispersion. The Jarque-Bera test results indicate significant deviations from normality for all variables, as denoted by p-values of .00, which reject the null hypothesis of normality at the 5% significance level. Finally, the kurtosis values suggest heavy tails in the variable distributions.

Table 4. ADF test results

ADF Test	Variable								
	r_ETH	r_BNB	r_SOL	r_TRX	r_BTC	d_ETH_TM	d_BSC_TM	d_SOL_TM	d_TRON_TM
With Constant	-(36.26) .00***	-(37.36) .00***	-(35.29) .00***	-(39.12) .00***	-(35.60) .00***	-(43.68) .00***	-(46.01) .00***	-(13.17) .00***	-(46.34) .00***
With Constant & Trend	-(36.25) .00***	-(37.35) .00***	-(35.28) .00***	-(39.11) .00***	-(35.69) .00***	-(43.66) .00***	-(46.10) .00***	-(13.20) .00***	-(46.33) .00***
Without Constant & Trend	-(36.27) .00***	-(37.36) .00***	-(35.27) .00***	-(39.13) .00***	-(35.61) .00***	-(43.69) .00***	-(46.02) .00***	-(13.17) .00***	-(46.35) .00***

Note. The values in parentheses "() "denote the t-statistics of the test. The asterisks "***" denote significance at the 1% level.

In Table 4, the results of the tests show that the null hypothesis of the presence of a unit root is rejected in all cases, denoting that the variables under examination are suitable to be included in the estimated GARCH models.

4.2. GARCH model results

In this section, we present the results of the examined models.

Table 5. Estimated models results

Variable	Dependent variable							
	r_ETH				r_BNB			
	Coefficient	Std. Error	z-Statistic	Prob.	Coefficient	Std. Error	z-Statistic	Prob.
r_ETH					.38	.05	7.85	.00***
r_BNB	.26	.03	8.05	.00***				
r_SOL	.12	.02	7.16	.00***	.06	.02	2.55	.01**
r_TRX	.08	.02	3.68	.00***	.11	.03	4.00	.00***
d_ETH_TM	-.63	.05	-13.53	.00***	.26	.06	4.36	.00***
d_BSC_TM	.18	.03	5.11	.00***	-.59	.06	-10.32	.00***
d_SOL_TM	.04	.01	3.04	.00***	.02	.02	.90	.37
d_TRON_TM	.03	.02	1.46	.14	.02	.03	.83	.40
r_BTC	.48	.03	13.97	.00***	.19	.04	5.31	.00***
c	.00	.00	-.88	.38	.00	.00	-.67	.50
AR(1)					.06	.04	1.46	.14

	Variance equation							
ω	.00	.00	1.81	.07*	.00	.00	1.17	.24
Alpha	.14	.05	2.76	.01***	.08	.03	2.38	.02**
Beta	.73	.11	6.79	.00***	.91	.04	22.54	.00***
	Dependent variable							
Variable	r_SOL				r_TRX			
	Coefficient	Std. Error	z-Statistic	Prob.	Coefficient	Std. Error	z-Statistic	Prob.
r_ETH	.51	.11	4.51	.00***	.23	.04	5.24	.00***
r_BNB	.30	.07	4.19	.00***	.08	.03	2.59	.01***
r_SOL					.06	.02	2.72	.01***
r_TRX	.17	.07	2.60	.01**				
d_ETH_TM	.34	.10	3.62	.00***	.18	.05	3.54	.00***
d_BSC_TM	.11	.07	1.66	.10*	.00	.03	.14	.89
d_SOL_TM	-.43	.06	-7.19	.00***	.02	.02	.86	.39
d_TRON_TM	.03	.04	.83	.41	-.42	.07	-5.92	.00***
r_BTC	.24	.10	2.41	.02**	.21	.05	4.14	.00***
c	.00	.00	-.30	.76	.00	.00	.17	.86
AR(1)	.10	.04	2.32	.02**				
AR(2)					.10	.04	2.18	.03**
	Variance equation							
ω	.00	.00	1.38	.17	.00	.00	1.07	.28
Alpha	.17	.08	2.11	.04**	.06	.05	1.23	.22
Beta	.82	.09	9.20	.00***	.93	.05	19.54	.00***

Note. The asterisks denote significance levels: *p < .10. **p < .05. ***p < .01.

In Table 5, we observe that for the model with *r_ETH* as the dependent variable, all the coefficients in the conditional mean are positive except for the *d_ETH_TM*, which is negative. Additionally, the constant and *d_TRON_TM* are not statistically significant. Furthermore, the alpha and beta coefficients in the variance equation are statistically significant, indicating that past shocks and past variances are significant predictors of current volatility.

Next, for *r_BNB*, the coefficients of *r_SOL*, *r_TRX*, *d_ETH_TM*, and *d_TRON_TM* are positive and statistically significant. The *d_BSC_TM* is significant and negative. The variance equation shows that the alpha and beta coefficients are statistically significant, suggesting persistence in volatility.

For *r_SOL*, the variables *r_ETH*, *r_BNB*, *d_ETH_TM*, *r_BTC*, *AR(1)* are positive and statistically significant. The *d_SOL_TM* is significant and negative. The variance equation shows that alpha and beta are statistically significant, indicating the importance of past shocks and variances.

For *r_TRX*, all variables are statistically significant except for *d_BSC_TM*, *d_SOL_TM*, and the constant. Notably, the *d_TRON_TM* variable has a negative coefficient. Only the beta term is statistically significant in the variance equation, suggesting that past variances are crucial in predicting current volatility.

5. Discussion

The results regarding the impact of the examined variables on the dependent variables are mixed. The *d_ETH_TM* is significant in all cases, showing the importance of this ratio in all the examined token returns. The returns of Bitcoin confirm the importance of its effect on the returns of the examined token prices. An interesting finding is that the returns of *d_TRON_TM* seem insignificant for the returns of the examined models, except for *r_TRX*. While the TRON network has a high TVL, its T/M ratio does not seem to affect the returns of the other tokens.

Notably, tokens' T/M ratios within their respective networks consistently exhibit negative and significant relationships with a high coefficient. Conversely, other T/M ratios demonstrate a positive correlation with the returns of the dependent variables. One possible explanation is that when a token's price and, consequently, its MCAP decrease, the T/M ratio increases. Additionally, as the TVL rises, volatility and expected returns on the token's price may decline, leading investors to seek more profitable opportunities elsewhere. Moreover, as the token price increases, investors might withdraw assets from the decentralized applications of its network to invest in the native token, which could offer greater profit potential as the price rises, or they may increase their holdings of stablecoins within the TVL to deposit them in yield-generating protocols, as the price decreases. However, given the comovement within the crypto market mainly influenced by Bitcoin (De Pace & Rao, 2023;

Kumar & Ajaz, 2019), a similar pattern should be anticipated with other networks' T/M ratios. This observation suggests that stablecoins locked in decentralized applications may have a relatively stable impact on a network's TVL, underscoring the importance of monitoring their presence, as they represent a relatively stable form of liquidity, and their token prices do not fluctuate. While the book-to-market ratio is positively related to the average stock returns in numerous studies (Araújo & Machado, 2018; Fama & French, 1992, 1995), this research has shown that it does not possess the same properties as the T/M ratio has on the respective token returns; therefore, these two ratios cannot be referred as equivalent.

The findings of this study differ from those of Şoiman et al. (2023) in both outcomes and methodology, as our research employs daily observations of the most valuable tokens based on MCAP and TVL while also integrating the dynamics of volatility into the model, aiming to explore the relationships between their ratios and returns.

Future research could include introducing a new metric to calculate the ratio of stablecoins locked within the network to its MCAP, which could prove valuable for tracking stablecoin liquidity, potentially offering analysts more profound insights. Finally, investigating the ideal level of a token's T/M ratio could aid in assessing token valuations and optimizing token portfolio construction, providing insights into a token's fundamental value, adoption, and risk when considering tokens for a portfolio.

6. Conclusion

This study analyzed the relationship between the T/M ratio and the daily returns of four major tokens from March 2021 to June 2024 while investigating the comovements among the other tokens and their respective T/M ratios. The results revealed a negative correlation between token returns and their own T/M ratios but a positive correlation with other tokens' returns and T/M ratios. These findings highlight distinct dynamics between the T/M ratio and token returns, suggesting that this ratio behaves differently from the book-to-market ratio concerning stock returns. As a result, direct comparisons are not applicable, underscoring the T/M ratio's unique characteristics and the need for further research in this area.

Authors Contributions

The authors contributed equally to the study.

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Competing Interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

References

Araújo, R. C. da C., & Machado, M. A. V. (2018). Book-to-Market Ratio, return on equity and Brazilian Stock Returns. *RAUSP Management Journal, 53*, 324-344. https://doi.org/10.1108/RAUSP-04-2018-001

Awyong, A. (2022). *The Role of Disclosure in DeFi Markets: Evidence from Twitter*. Working paper.

Bhambhwani, S. M., & Huang, A. H. (2024). Auditing decentralized finance. *The British Accounting Review, 56*(2), 101270. https://doi.org/10.1016/j.bar.2023.101270

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics, 31*(3), 307-327. https://doi.org/10.1016/0304-4076(86)90063-1

Cryptocurrency Prices, Charts, and Crypto Market Cap. (n.d.). *CoinGecko*. Retrieved October 26, 2023, from https://www.coingecko.com/

Dahlberg, T., & Dabaja, F. (2021). *Decentralized Finance and the Crypto Market: Indicators and Correlations*. Retrieved from https://urn.kb.se/resolve?urn=urn:nbn:se:liu:diva-177960

De Pace, P., & Rao, J. (2023). Comovement and instability in cryptocurrency markets. *International Review of Economics & Finance, 83*, 173-200. https://doi.org/10.1016/j.iref.2022.08.010

DefiLlama. (n.d.). *DefiLlama—DeFi Dashboard.* Retrieved October 23, 2023, from https://defillama.com/

Fama, E. F., & French, K. R. (1992). The Cross-Section of Expected Stock Returns. *The Journal of Finance, 47*(2), 427-465. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

Fama, E. F., & French, K. R. (1995). Size and Book-to-Market Factors in Earnings and Returns. *The Journal of Finance, 50*(1), 131-155. https://doi.org/10.1111/j.1540-6261.1995.tb05169.x

Grigorova, I., Karamfilov, A., Merakov, R., & Efremov, A. (2024). Simulation of Dynamic Performance of DeFi Protocol Based on Historical Crypto Market Behavior. *Risks*, *12*(1). https://doi.org/10.3390/risks12010003

Ke, P. F., & Ng, K. C. B. (2022). *Bank error in whose favor? A case study of decentralized finance misgovernance*. Retrieved from https://ink.library.smu.edu.sg/sis_research/7681

Likhitha, B. B., Raj, C. H. A., & Islam, M. S. U. (2023). Unveiling Ethereum's Future: LSTM-Based Price Prediction and a Systematic Blockchain Analysis. *E3S Web of Conferences*, *453*, 01043. https://doi.org/10.1051/e3sconf/202345301043

Luo, Y., Feng, Y., Xu, J., & Tasca, P. (2024). *Piercing the Veil of TVL: DeFi Reappraised* (arXiv:2404.11745). arXiv. https://doi.org/10.48550/arXiv.2404.11745

Maouchi, Y., Charfeddine, L., & El Montasser, G. (2022). Understanding digital bubbles amidst the COVID-19 pandemic: Evidence from DeFi and NFTs. *Finance Research Letters, 47,* 102584. https://doi.org/10.1016/j.frl.2021.102584

Moro-Visconti, R., & Cesaretti, A. (2023). Digital Token Valuation: Looking for a New Gold Standard? In R. Moro-Visconti & A. Cesaretti (Eds.), *Digital Token Valuation: Cryptocurrencies, NFTs, Decentralized Finance, and Blockchains* (pp. 355-393). https://doi.org/10.1007/978-3-031-42971-2_11

S Kumar, A., & Ajaz, T. (2019). Co-movement in crypto-currency markets: Evidences from wavelet analysis. *Financial Innovation*, *5*(1), 33. https://doi.org/10.1186/s40854-019-0143-3

Şoiman, F., Dumas, J. G., & Jimenez-Garces, S. (2023). What drives DeFi market returns? *Journal of International Financial Markets, Institutions and Money, 85*, 101786. https://doi.org/10.1016/j.intfin.2023.101786

Stepanova, V., & Eriņš, I. (2021). Review of Decentralized Finance Applications and Their Total Value Locked. *TEM Journal, 10*(1). https://doi.org/10.18421/tem101-41