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Tokenomics in the Metaverse: understanding the lead–lag effect among emerging crypto tokens

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Abstract

The convergence of blockchain and immersive technologies has resulted in the popularity of Metaverse platforms and their cryptocurrencies, known as Metaverse tokens. There has been little research into tokenomics in these emerging tokens. Building upon the information dissemination theory, this research examines the role of trading volume in the returns of these tokens. An empirical study was conducted using the trading volumes and returns of 197 Metaverse tokens over 12 months to derive the latent grouping structure with spectral clustering and to determine the relationships between daily returns of different token clusters through augmented vector autoregression. The results show that trading volume is a strong predictor of lead–lag patterns, which supports the speed of adjustment hypothesis. This is the first large-scale study that documented the lead–lag effect among Metaverse tokens. Unlike previous studies that focus on market capitalization, our findings suggest that trade volume contains vital information concerning cross-correlation patterns.

Keywords: Tokenomics, Lead–lag, Metaverse tokens, Trade volume, Daily returns

Introduction

Since Bitcoin's debut in 2008, many new types of cryptocurrency have emerged. From stable coins to non-fungible tokens (NFTs) to dog memes, a wide variety of cryptocurrencies are available today(Kou 2019). CoinMarketCap reports that there are approximately 22,360 cryptocurrencies, with a total market capitalization of $1.04 trillion.[1] Within the spectrum of various cryptocurrencies, a distinct category of tokens, denoted as Metaverse tokens, has garnered considerable interest from both scholarly investigators and investment practitioners.

The Metaverse is a term used to describe a virtual world or universe where people can interact and engage with each other in a variety of ways (Cheng et al. 2022; Kraus et al. 2022). It is often associated with virtual reality, augmented reality, and other forms of digital world-building. Metaverse tokens are digital assets that can be used within these virtual worlds to buy and sell virtual goods, access premium content or services,

[1] Data retrieved from https://coinmarketcap.com/, on 28 Jan 2023.

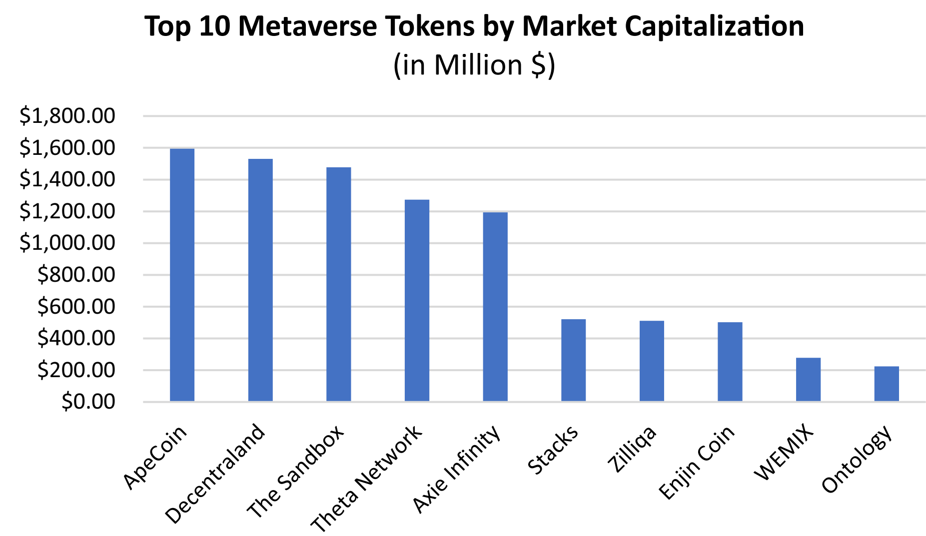

Fig. 1 Top 10 Metaverse tokens by market capitalization Source: coinmarketcap (2022)

or represent ownership of virtual real estate(Vidal-Tomás 2022). Metaverse tokens are special because they have the potential to enable a new type of digital economy within virtual worlds and allow for the creation of new business models and revenue streams within the metaverse. As the Metaverse domain gains momentum, a surge in investment and substantial capital influx into these cryptographic tokens is anticipated. Consequently, comprehending the valuation mechanisms of these tokens becomes imperative to protect the interests of the broader community, encompassing users, investors, and developers within the Metaverse realm (Vidal-Tomás 2023).

The Metaverse token market is still relatively new and emerging, but it has seen significant growth in recent years. Some of these tokens have seen impressive price gains, due to the increasing interest in virtual worlds and the potential for these tokens to be used in various ways within the Metaverse (Vidal-Tomás 2022). Currently, there are more than 200 different Metaverse tokens that are actively traded in the crypto market daily and they vary in size as measured by the total market capitalization. Figure 1 below shows the top 10 crypto tokens used for Metaverse platforms in terms of market capitalisation. Some of the leading coins have a total market value as high as 1.6 billion dollars, which is comparable to that of a small-medium-sized publicly listed company in the real world (coinmarketcap 2022).

Similar to stock prices, the Metaverse token prices are volatile and are affected by many economic and financial factors (Cong et al. 2021 2022). The studies on the price movements of these crypto tokens are some of the most tracked themes in the research on Metaverse (Hu et al. 2019a b; Urquhart 2016; Zargar and Kumar 2019). However, in the past, most crypto market research has focused on the industry's heavyweight tokens, such as Bitcoin and Ethereum (Le Tran and Leirvik 2020). There has been very little research into tokenomics in the Metaverse field and almost no studies covering the smaller-sized tokens.

Building upon the information dissemination theory, this research examines the role played by trading volume in predicting future returns of Metaverse crypto tokens.

We conducted an empirical study to determine whether the daily returns of leading Metaverse tokens are cross-correlated with the values of follower tokens at later times, using 197 Metaverse token prices and trading volume over 12 months. The empirical results show that such lead–lag effect[2] does exist among Metaverse crypto tokens, and that trading volume is a strong predictor of the observed lead–lag patterns. These patterns emerge because low-volume tokens' returns respond to market information more slowly, which provides support to the speed of adjustment hypothesis.

This research contributes to the study of token economy in several aspects: Firstly, unlike previous research that zooms into only a handful of major heavyweight cryptocurrencies (Le Tran and Leirvik 2020; Sifat et al. 2019), this is the first full-scale study to document the lead–lag effect that applies to most tokens within the Metaverse token category. Secondly, in contrast to previous studies that focus on market capitalisation, our findings suggest that trade volume contains vital information concerning cross-correlation patterns. Returns on Metaverse tokens with high trading volume lead returns on stocks with low trading volume, owing to the fact that high-volume Metaverse tokens respond to marketwide information faster. This is of paramount importance to both Metaverse users and token investors. Thirdly, in terms of methodology, the research marks the first attempt to use spectral clustering to model the latent grouping structure of cryptocurrencies. Our research shows that such a framework deployed for time series clustering via spectral decomposition of the affinity matrix is appropriate and effective in determining cluster membership. Lastly, our research also offers practical implications in terms of trading strategies for Metaverse investors and sectoral supervisory approach for regulatory authorities as our findings suggest that trade volume contains vital information concerning cross-correlation patterns. The predictability of Metaverse token returns provides insight into risk propagation and investment market segmentation.

Literature review

Tokenomics, a portmanteau of "token" and "economics", is used to describe all aspects of a token's economic model, including a token's use and value, including its creation and distribution, supply and demand, incentivizing mechanisms, etc. (Cong et al. 2021). The main difference from the traditional economy is that tokenomics are designed specifically for decentralised crypto networks or ecosystems, such as major Metaverse platforms represented by the Decentraland with the token MANA and the Sandbox with the token SAND (Guan et al. 2022).

Naturally, practitioners and economists are intrigued with the tokenomics design, and literature discussing the framework and structure of tokenomics has been burgeoning. For example, Freni et al. (2022) discussed the paradigmatic shifts from economics to tokenomics and Carvalho (2022) compares the effects of tokens' economics to the foundational concepts in finance such as shares, profits, or dividends. Lo and Medda (2020), via an empirical study on venture-related blockchain tokens, find evidence that the functions of a token create an economic link between the blockchain project and the token price—different functional types of blockchain tokens are associated with statistically

[2] Lead-lag effect is commonly used in finance to describe the phenomenon where one security leads the price movement of another, with some time delay.

significant differences in token prices. Lo and Medda (2020) argue that this finding provides justification for recent regulators' action of differentiating security tokens and utility tokens and regulate differently.

Lo and Medda (2020) are not the only or the first researcher who touched on what impact or even determine cryptocurrency prices. Valuation and market efficiency are evergreen topics among economics and finance researchers, and with the exponential growth of cryptocurrency market capitalization and trading volumes in the past years, empirical studies examining cryptocurrency prices already emerged. Earlier studies mostly concluded that the cryptocurrency markets were far from efficient. Urquhart (2016) was arguably the first to test the weak form of Bitcoin data and he concluded that Bitcoin returns are market inefficient. Zargar and Kumar (2019) used high-frequency data to test the martingale hypothesis in Bitcoin returns and found evidence of the presence of informational inefficiency in the Bitcoin market at higher frequency levels. Hu et al. (2019a b) ran various panel tests on cryptocurrencies but found no empirical support for the Efficient Market Hypothesis either. This is understandable given that cryptocurrencies, mostly Bitcoin and Ethereum, were still relatively small in terms of market capitalization and that the numbers of users and traders were rather limited.

A turning point probably took place when Le Tran and Leirvik (2020) examined the level of market efficiency in the five largest cryptocurrencies and reported that the efficiency is highly time-varying. They found evidence that these cryptocurrency markets had become more efficient in the period of 2017–2019. As time went by and more market data became available, tokenomics models also started to emerge.

Among the sparse equilibrium models on tokenomics, probably the most noteworthy is the one built by Cong et al. (2021 2022). Their model captures two key features shared by tokenomics: firstly, tokens are the means of payment on platforms and they support economic transactions on the platforms. Secondly, the user adoption of a platform exhibits a network effect: the more users participate on a platform, the easier it is for any user to find a transaction counterparty, and this will make the token more useful and raise the expected future token price.

Their model is constructed in such a way that the transaction benefits of tokens will increase if people expect the platform's future productivity to rise, which will attract more users. The larger user base will subsequently increase transaction benefits due to the user network externality and drive up the token prices and even greater adoption in the future.

Cong et al. (2021)'s model carries a few important implications that could be tested empirically: First of all, users can conduct peer-to-peer transactions on digital platforms such as the Metaverse, and the equilibrium price of tokens is determined by aggregating heterogeneous users' transactional demand. This suggests that trading volume could matter, as it is an intuitive proxy for transactional demand.

In addition, their model focuses on the endogenous formation of the platform, where the two key endogenous variables are the token price and platform user base. As previously discussed, the user base captures the positive network externality of user adoption and impacts token prices positively. This intertemporal feedback between token price and user adoption implies that the price discovery might not be done instantaneously in Metaverse. As information diffusion might take time by design, it also poses an interesting question on if there will delay in information diffusion across different Metaverse tokens.

Cong et al. (2021) also pointed out that the existence of asymmetric information may cause financial friction. For example, on certain less decentralized platforms, only platform managers can see the fee flows, and the fee-based payouts to investors are subject to moral hazard risk. The model, therefore, features a tractable, static form of incomplete information. This could be another reason for delayed information transmission. An empirical investigation into how information is transmitted within crypto markets is called for in order to understand the pricing and market efficiency of Metaverses.

With a unique database that covers almost the complete set of Metaverse tokens, we are able to conduct such an empirical test and shed light on the information diffusion process in Metaverses. Specifically, due to the endogeneity of tokenomics and friction caused by asymmetric information in metaverses, information diffusion will not be instantaneous and we expect to observe lead–lag effect, a.k.a., the returns of some tokens are cross-correlated with those of other tokens at later times.

We are also able to examine the potential role of user adoption in tokenomics pricing discovery, as modeled by Cong et al. (2021). Intuitively we use trading volume as a proxy for user adoption—if the network effect of user adoption is valid, we expect to see tokens with higher trading volume lead the others.

Our hypothesis is therefore formulated as:

Hypothesis 1 The returns of Metaverse tokens with higher trading volume are cross-correlated with those of Metaverse tokens with lower trading volume at later times.

The hypothesis will be validated if we observe lead–lag effect among the Metaverse tokens and if the trading volume has predicting power over such an effect.

It is worth noting that our hypothesis is also consistent with the differential speed of adjustment argument in conventional financial studies, where researchers usually regard lead–lag effect as evidence that information diffusion takes time in a less-than-perfectly-efficient market. For instance, Lo and MacKinlay (1990) find that the returns of large stocks lead those of smaller stocks, and Chordia and Swaminathan (2000) observe the lead–lag effect of short-term returns between high-volume portfolios and low-volume portfolios. Chordia and Swaminathan (2000) argue that this is because returns on low-volume portfolios respond more slowly to information in market returns. Similarly, Hou (2007) finds that the lead–lag effect between big firms and small firms is more evident within industries, and he believes that the slow diffusion of industry information is a leading cause of the lead–lag effect.

It will be really interesting therefore to see if the lead–lag effect exists in crypto tokens, and our study is among the first to formally examine the lead–lag effect in crypto-tokens on a large scale. Some existing literature looks into the cross-correlation of cryptocurrencies but most of them focus on the major ones such as Bitcoin and Ethereum. For example, Sifat et al. (2019) investigate the lead–lag relationship between Bitcoin and Ethereum and found evidence of bi-directional causality between the two assets. Hu et al. (2019a b) report evidence that the market returns of all other coins are strongly correlated with Bitcoin returns. Vidal-Tomás (2022) on the other hand, seems to find evidence that Metaverse and play-to-earn tokens are only weakly correlated to a crypto market benchmark index, predominantly consisting of Bitcoin and Ethereum. None of the studies consider the cross-sectional correlations among tokens other than Bitcoin and Ethereum, let alone the timing differences. We expect to provide empirical results on the potential lead–lag relationships of Metaverse crypto tokens and close the gap between conventional financial markets and crypto markets. In addition, as Metaverses are still a nascent yet fast-growing industry and attract a lot of attention from researchers, investors and regulatory bodies, empirical evidence on lead–lag effect (or the lack of it) will provide us with important implications and guidance for future practices.

Methods

We collected the daily price series of 197 Metaverse tokens from the Investing.com database using investpy—an extensible and open Python package for data extraction (del Canto 2021). Investing.com represents one of the highly-referenced price-tracking platforms among the scholarly community (Alves et al. 2020; Hernández-Nieves et al. 2021), which covers crypto assets (El-Berawi et al. 2021) and other asset classes (Liu et al. 2017). With Metaverse being the "Year in a Word 2021" by the Financial Times (Waters 2021), the sampled time period (all trading days between March 21, 2021, and March 20, 2022) was chosen because it captures the entire duration of the Metaverse hype before the crypto crash in 2022 (see Fig. 2 for the Google search trends of "metaverse"), which allows a reasonably sufficient amount of time lag for information diffusion and market responses. Three data time series were obtained for each token entry: the daily opening prices, the daily closing prices, and trading volumes, and the daily returns are derived from the daily opening prices and the daily closing prices.

We conducted an empirical study to determine whether the daily returns of the leading tokens are cross-correlated with the values of follower tokens at later times, using Metaverse token prices from Investing.com. Our study is carried out in two phases to investigate the hypothesized effects. Phase 1 used spectral clustering to categorise Metaverse tokens against the similarity in trading volume patterns, extending the approaches by Shi and Malik (2000). Spectral clustering, which is based on algebraic graph theory, has piqued the interest of academia in recent years due to its strong theoretical foundations as well as the capability of processing the time series with high dimensions and dealing with arbitrarily shaped datasets (Cai et al. 2011; Damle et al. 2019; Shang et al. 2016; Von Luxburg 2007). This approach may be used to locate normalized graph cuts if the affinity matrix is the graph's adjacency matrix (Shi and Malik 2000). Its results frequently surpass traditional algorithms such as k-means or methods using a single linkage, especially when the structure of the individual clusters is significantly non-convex, such as when clusters are nested circles on the plane (Von Luxburg 2007).

Spectral clustering is deployed to find a balanced grouping with adequate homogeneities regarding the degree of correlation(Von Luxburg 2007). Spectral clustering is useful when the data points are not easily separated by a straight line or hyperplane or when the clusters have non-convex shapes. It is particularly useful for time series data, which may have complex patterns that are not easily captured by linear methods such as k-means

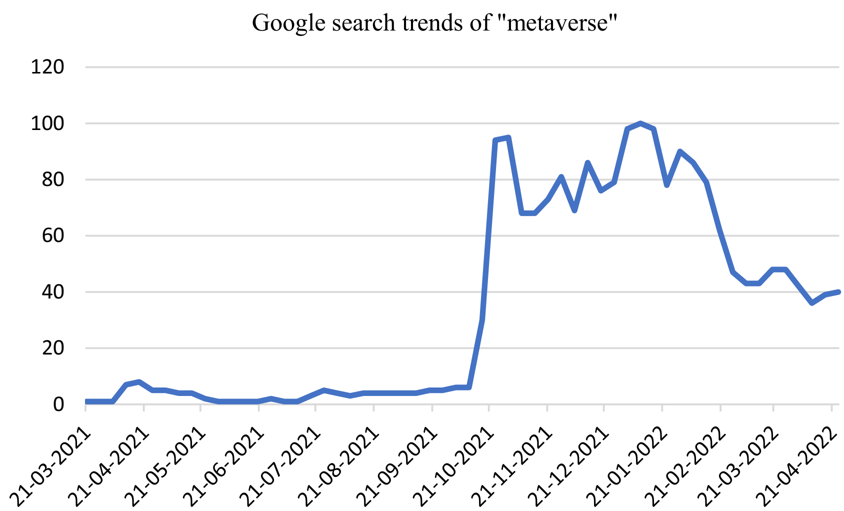

Fig. 2 Google search interest during the sample time period

and hierarchical clustering which do not perform well in high-dimensional spaces (Ng et al. 2001). Our dataset is a '197 × 365' matrix, each row of the matrix represents a time series of token volume, with 365 observations (days) in each series. By examining the probability density function of the data via kernel density estimation (KDE) test, the data contains regions of high density that are not easily separated by a linear boundary (Scott 2015). As a result, it prompts us to consider spectral clustering as the top option. However, we compared the performance of spectral clustering with k-means with Dynamic time warping (DTW) distance and hierarchical clustering (Keogh and Lin 2005; Salvador and Chan 2007). We found that k-means and hierarchical clustering are not able to separate the tokens into meaningful clusters, given they assigned 195 tokens into one cluster and identified one cluster for each of the remaining tokens. In addition, spectral clustering is not sensitive to the initial conditions as k-means, it is also less sensitive to the presence of noise or outliers in the data, and it can be used with a wide range of similarity measures, such as the Gaussian kernel or the cosine similarity(Von Luxburg 2007). Another advantage of spectral clustering is that it can handle data with arbitrary shape and size, which is useful for time series data where the number of data points may vary from one series to another (Von Luxburg 2007; Wang & Zhang 2005). This aligns with our dataset in the study, where trading periods for the 197 tokens differ. The minimum number of trading days is 0, while the maximum is 365 days, with a mean value of 168.13 days and a standard deviation of 122.22 days. Some tokens are actively traded almost every day (e.g., Decentraland, Aavegotchi, The Sandbox Coin), while others experience a decrease in trading volume and eventually vanish over time (e.g., DeNations, Bullieverse). Additionally, some tokens have sparse trading days (e.g., Somnium Space Cubes), and others started trading later but persisted for an extended duration (e.g., Torum).

Using the Gaussian kernel, a distance matrix with zero indicating identical elements and high values indicating significantly different components can be turned into an affinity or similarity matrix suitable for the procedure with a k-nearest neighbours connection matrix (Yu and Shi 2003). The inputs for the normalized spectral

Table 1 Summary statistics of token clusters

Category	Observations	Mean trading Volume (USD in Millions)	Std. dev (USD in Millions)	Min (USD in Millions)	Max (USD in Millions)	Skewness	Kurtosis
Cluster 1 Leading	58	36.69	34.89	2.01	266.80	2.36	8.35
Cluster 2 Follower	111	0.35	0.27	0.04	1.24	0.89	-0.14
Cluster 3 Outlier	28	0.004	0.04	0.00	0.73	18.05	336.21
Grand Total	197	11.00	10.36	0.63	78.95	2.33	8.17

clustering described by Shi and Malik (2000) are the similarity matrix $S \in \mathbb{R}^{n \times n}$ and the number k ($k = 3$) of clusters. It begins by constructing a similarity graph using k -nearest neighbour graphs. W represents the weighted adjacency matrix. The unnormalized Laplacian L is then computed, followed by the initial generalized eigenvectors $u_1, \ldots, u_k$ of the generalized eigenproblem $L_u = \lambda D_u$. $U \in \mathbb{R}^{n \times k}$, is the matrix with the vectors $u_1, \ldots, u_k$ as columns. The vectors $y_i \in \mathbb{R}^k$ corresponds to the $i - th$ row of U, $i = 1, \ldots, n$. Finally, the points y_i in $\mathbb{R}^k$ are grouped into $C_1, \ldots, C_k$. The analysis identifies three distinct clusters, i.e., a "leading" cluster, a "follower" cluster, and an "outlier" cluster. The descriptive statistics are shown in Table 1.

Phase 2 investigated how trading volume affects the return of Metaverse crypto tokens by comparing the token performance across the three groups derived from Phase 1. We modeled the pair-wise lead–lag effect between clusters of tokens using an augmented Vector Autoregression (VAR) model, where the weighted average daily returns of the three clusters of tokens are analyzed in pairs. The variables in our model are in the form of time series and are autocorrelated. The VAR model is used as a logical extension of the univariate autoregressive model due to its flexibility and capacity to quantify the causal effects among dynamic multivariate time series. It has been widely adopted in studies of policy analysis, macroeconomic planning, and financial markets to investigate the causal relationships among variables such as economic growth, inflation, imports, exports, exchange rate, oil prices, and stock prices (Hsu et al. 2008; Lütkepohl 2005; Siggiridou and Kugiumtzis 2015; Tsay 2005). The analyses in the two stages built on each other, lending credence to the idea that follower tokens tend to partially replicate the performance fluctuations of the leading tokens in subsequent periods.

The VAR model, a multivariate time series model, is to explain the dynamic relationships between various variables (Lütkepohl 2005). The model is frequently used in econometrics and finance to examine how various variables relate to one another through time and forecast future value (Enders 2010). The Toda-Yamamoto (TY) specification is used to determine the direction of causality between two time series variables. It is based on the idea of testing the significance of lagged variables in a VAR model (Toda and Yamamoto 1995). In the TY procedure, the VAR model captures the linear interdependence between the two time series, and the TY procedure tests for causality by examining the impulse response functions and forecast error variance decompositions of the VAR model (Toda and Yamamoto 1995).

Following the TY procedure, we build Eqs. (1) and (2) to examine the pair of a causal relationship between leading tokens and follower tokens as discussed in the first step. In the Eq. (1), F_t and L_t are vectors of time series variables. L_t denotes the daily return of leading tokens (Group 1). F_t represents the daily return of follower tokens (Group 2). p denotes the lag order; a_i and b_i are parameters to be estimated, a_0 is the constant term and u_t is the error term. The VAR (p) specification of the model implies that each variable depends on its own lags and the lags of the other variables up to order p. For Eq. (1), the null hypothesis is $H_0 : b_1, \ldots, and b_p$ are all equal to zero, while the alternative hypothesis H_A is "Not H_0." F_t Granger causes L_t if H_0 may be rejected. We may learn from the test if leaders' returns are better predicted by their own histories and the histories of their followers' returns than by their own histories alone. Similarly, c_i and d_i are parameters to be estimated, c_0 is the constant term and v_t is the error term in Eq. (2). H_0 is $d_1, \ldots, and d_p$ are all zero in Eq. (2), but H_A is "Not H_0." L_t does not Granger-cause F_t if H_0 cannot be rejected. We may learn from the test if followers' token returns are better predicted by their own histories and the histories of leaders' returns than by their own histories alone.

$$L_t = a_0 + a_1 L_{t-1} + \ldots.. + a_p L_{t-p} + b_1 F_{t-1} + \ldots.. + b_p F_{t-p} + u_t \tag{1}$$

$$F_t = c_0 + c_1 F_{t-1} + \ldots.. + c_p F_{t-p} + d_1 L_{t-1} + \ldots.. + d_p L_{t-p} + v_t \tag{2}$$

Second, we also use equations to test causality between leading tokens and outlier tokens as denoted in Eqs. (3) and (4). $\mathrm{L_t}$ represents the daily return of leading tokens (Group 1). $\mathrm{O_t}$ represents the daily return of outlier tokens (Group 3). e_i and f_i are parameters to be estimated, e_0 is the constant term and ε_t is the error term in Eq. (3). For Eq. (3), the null hypothesis is $H_0 : f_1, \ldots, and f_p$ are all equal to zero, while the alternative hypothesis H_A is "Not H_0." O_t Granger causes L_t if H_0 may be rejected. We may learn from the test if leaders' returns are better predicted by their own histories and the histories of the outliers' returns than by their own histories alone. g_i and h_i are parameters to be estimated, g_0 is the constant term and η_t is the error term in Eq. (4). H_0 is $h_1, \ldots, and h_p$ are all zero in Eq. (4), but H_A is "Not H_0." L_t does not Granger-cause O_t if H_0 cannot be rejected. We may learn from the test if outliers' token returns are better predicted by their own histories and the histories of leaders' returns than by their own histories alone. Finally, another set of equations, represented by Eqs. (5) and (6), is utilized to examine the causal links between follower tokens and outlier tokens.

$$L_t = e_0 + e_1 L_{t-1} + \ldots.. + e_p L_{t-p} + f_1 O_{t-1} + \ldots.. + f_p O_{t-p} + \varepsilon_t \tag{3}$$

$$O_t = g_0 + g_1 O_{t-1} + \ldots.. + g_p O_{t-p} + h_1 L_{t-1} + \ldots.. + h_p L_{t-p} + \eta_t \tag{4}$$

$$F_t = k_0 + k_1 F_{t-1} + \ldots.. + k_p F_{t-p} + m_1 O_{t-1} + \ldots.. + m_p O_{t-p} + \xi_t \tag{5}$$

$$O_t = n_0 + n_1 O_{t-1} + \ldots.. + n_p O_{t-p} + s_1 F_{t-1} + \ldots.. + s_p F_{t-p} + \delta_t \tag{6}$$

Results

Three clusters of tokens are identified through spectral clustering and the statistics of the clusters are summarized in Table 1. Cluster 1 (58 tokens) and Cluster 2 (111 tokens) are denoted as the "leading" and the "follower" clusters respectively, based on their average trading volumes. We verified the cluster membership of the mainstream Metaverse tokens such as Decentraland (MANA) Coin, The Sandbox (SAND) Coin, Axie Infinity (AXS) Coin, Enjin Coin, and WEMIX Coin, etc., and found that all these large tokens by market capitalization belong to the leading cluster. Refer to Annex for a list of abbreviations and definitions in full. The last cluster shown in Table 1 is the smallest in size (28 tokens) and sparse. Its summary statistics are markedly different from the other two clusters. Clustering-based outlier detection approaches assume that normal data belong to large and dense clusters, whereas outliers belong to small or sparse clusters (Cassisi et al. 2013). As a result, Cluster 3 is labeled as the "outlier" cluster. We calculated the Calinski–Harabasz Index for the outcomes of spectral clustering, offering a quantitative measure of the clustering effectiveness by assessing the compactness and separation of clusters. In comparison to K-means and hierarchical clustering, spectral clustering yielded a higher index value of 151.68. This result signifies that the algorithm has effectively generated well-defined clusters characterized by minimal within-cluster variance and maximal between-cluster variance. Hence, spectral clustering is deemed more successful in creating clusters that are both distinct and homogeneous.

After applying Spectral Clustering, we also analyse the structure of the similarity matrix and graph utilized in the algorithm to verify the results from the spectral clustering algorithm. The similarity matrix captures pairwise relationships between data points based on a chosen similarity measure. This matrix can be represented as a weighted graph, where each data point acts as a node, and the edge weights signify the similarity between the nodes. By examining the minimum spanning tree (MST), we gain valuable insights into the connectivity and relationships among the data points, as the MST connects all nodes without forming cycles. Figure 3 shows the spanning tree of spectral clustering. Through this exploration, clusters or subgroups of points emerge, exhibiting close connections based on their similarities. In the MST, we can observe long edges or bridges that link different parts of the tree. These edges are indicative of outlier nodes, potentially acting as bridges between distinct clusters or subgroups, such as the nodes in the "outlier" group. Additionally, we identify nodes with a high degree of centrality within the MST, representing hubs within a cluster. These central nodes play a significant role in maintaining connectivity within their respective clusters. Although an MST is by nature acyclic, the presence of loop-like or cyclic structures within it can suggest the existence of subgroups or clusters. These loops signify strong connections and cyclic relationships among a subset of nodes, potentially representing distinct clusters, such as the "leading" group and the "follower" group.

We also examine the trading volume patterns over the sampled period for all three clusters: leading tokens (Cluster 1), follower tokens (Cluster 2), and outlier tokens (Cluster 3), illustrated in Fig. 4. This graphical representation reveals that the trading volume of leading tokens was subdued from March to May, experienced an increase, and reached its initial peak in July 2021, followed by a significant decline from the peak in November 2021. The trading volume patterns among these three clusters exhibit a substantial

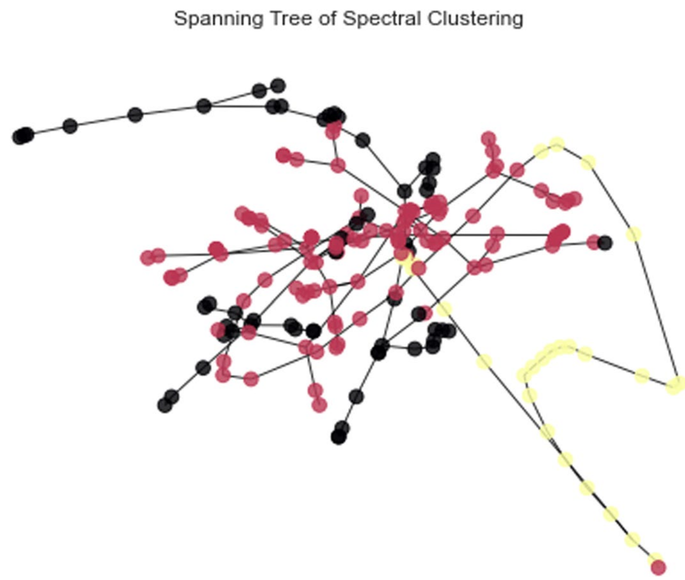

Fig. 3 Spanning tree of spectral clustering

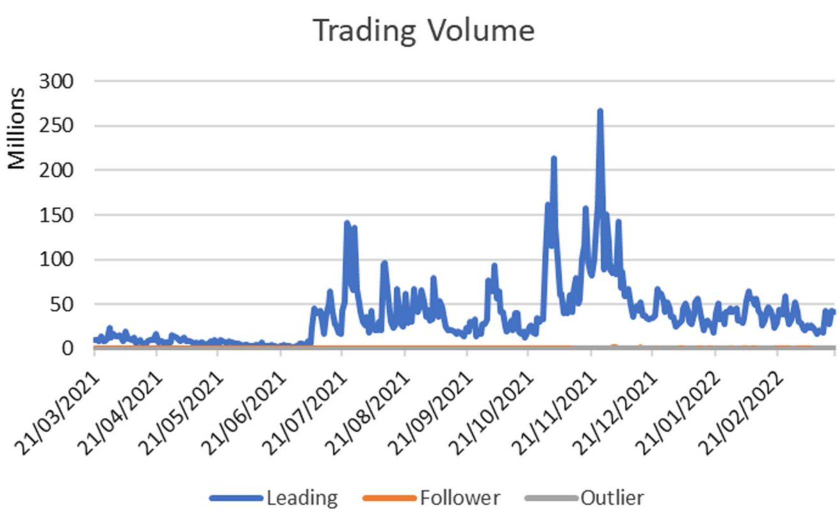

Fig. 4 Trading Volume across Clusters

difference, with a noticeable distinction in magnitudes. However, due to these magnitude differences, the patterns of follower and outlier clusters are not clearly observable in Fig. 3. Therefore, we visualize these differences by creating another line chart using a dual-axis approach in Fig. 4, which will be further explained in subsequent paragraph.

Additionally, T-test and one-way ANOVA test were conducted on the centroids of the three clusters. The centroids of Cluster 1 (leading) and Cluster 2 (followers) are statistically different, as confirmed by a T-test (p value < 0.001 and t-statistics = 19.87). A one-way ANOVA test was utilized to identify statistically different mean values among the centroids of the three clusters. The F-statistic for the one-way ANOVA was 394.78, and the associated p value < 0.001, indicating a statistically significant difference among the centroids. Both T-test and ANOVA tests were carried out using the Python library Scipy.

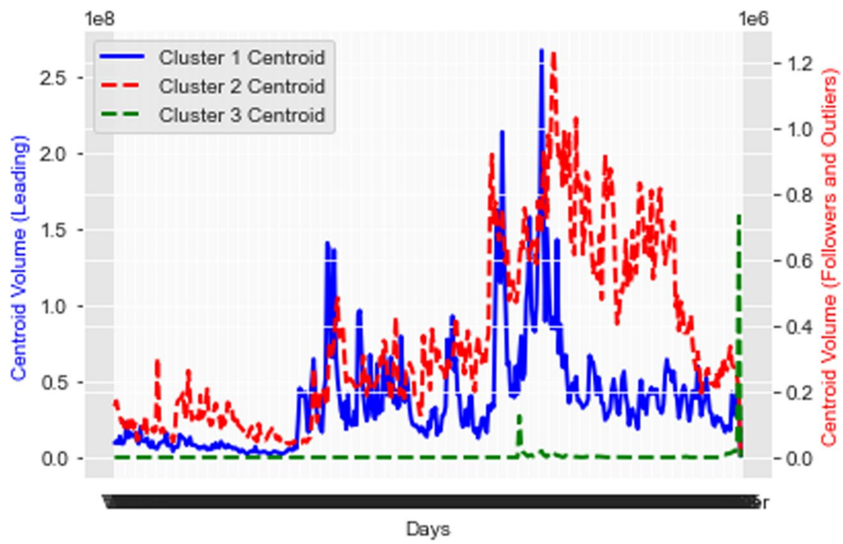

Fig. 5 Trading volume across clusters (dual axis)

The trading patterns are detailed and clarified in a dual-axis line chart in Fig. 5. The follower cluster mirrors the pattern of the leading cluster but on a smaller scale (with a 100-times difference in magnitude in the dual axis). The follower cluster exhibits lower volatility and demonstrates correlated patterns with the leading cluster. Notably, during the peak periods in July 2021 and November 2021, the follower cluster responded more slowly, climbing to lower levels than the leading cluster with noticeable lags. In contrast, the outlier cluster maintains minimal trading volume, remaining stagnant for the majority of the time, with a slight increase observed in November 2021. A comparison between the leading and follower clusters reveals observable correlations and similar patterns, prompting an in-depth exploration of the dynamics between these clusters. The primary inquiry revolves around determining whether there is significant causality between the time series of returns for leading and follower tokens.

Then, to validate H1, we further test the causality relationship between the daily returns of the leading Metaverse tokens and the daily returns of the follower tokens using the augmented VAR model. We applied the Toda and Yamamoto (TY) procedure, specifically designed for variables with unknown orders of integration. In contrast to the Johansen-Juselius method (Johansen and Juselius 1990), the TY approach eliminates the need for preliminary cointegration tests (Toda and Yamamoto 1995). Its utility is particularly notable when assessing both bilateral and unilateral causality, where time series exhibit different orders of integration. When reporting the results from the TY procedure, we first ensure the stationarity of time series data because the use of nonstationary time series could result in erroneous regression (He and Maekawa 2001). We conducted two distinct unit root tests for the assessment of our time series data. Employing both the Augmented Dickey–Fuller (ADF) test, which posits the null hypothesis of time-series non-stationarity, and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test, which posits the null hypothesis of time-series stationarity, and cross-verified the results. Table 2 presents the ADF and KPSS statistics results for the daily return of leading, follower, and outlier tokens. The outcomes indicate that the first-order difference renders

Table 2 Test of ADF and KPSS

Variable	Description	ADF test	KPSS test
L_t	Daily return of leading tokens	− 6.1817	0.3700
$D(L_t)$	Difference in daily return of leading tokens	− 10.8060**	0.0087
F_t	Daily return of follower tokens	− 4.9691	0.3249
$D(F_t)$	Difference in daily return of follower tokens	− 9.8679**	0.0094
O_t	Daily return of outlier tokens	− 5.3239	0.1091
$D(O_t)$	Difference in daily return of outlier tokens	− 8.5863**	0.0113

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

these time series stationary, thereby allowing us to infer the maximum order of integration for the VAR models (Toda and Yamamoto 1995).

As a next step, we test whether leading tokens exert effects on the follower tokens' returns. Specifically, increased (decreased) returns of leading tokens lead to higher (lower) returns of the follower tokens. Second, we observe if follower tokens fluctuations would affect the returns of leading tokens. The timing and length of the effects are also examined. Table 2 illustrates that the first-order difference of variables L_t, F_t, O_t eliminates the unit root for the three time series. As a result, the maximum order of integration is one, represented as I (1). Following that, the augmented VAR model is developed using the levels of the data. The appropriate lag for the variables is determined by the collective information indices of Akaike Information Criterion (AIC), Hannan Quinn (HQ), Schwarz Criterion (Hens and Schenk-Hoppé 2009), and Final Prediction Error (FPE). Based on the outcomes of these criteria, four lags are chosen. According to the TY procedure, a cointegration test is not needed to avoid pretest bias. However, the VAR model must be specified to guarantee that the residual value has no serial correlation. The Portmanteau test demonstrates that a lag of four removes serial autocorrelation in residuals for all equations. Through the tests for misspecification, a lag of five is used including one lag of the maximum order of integration to enter into each of the equations. Then, the augmented VAR model for Eqs. (1) to (6) is constructed accordingly with a Wald test. The test is to determine if the coefficients of the first four lagged L_t, F_t, or O_t values in the equations are zero. The lag of five is not included since the additional lagged value is used to fix asymptotics of the Wald test statistics. Rejection of the Wald test suggests the existence of Granger causality between the pair of variables.

Expectedly, Table 3 shows the mutual causality between leading tokens' returns and follower tokens' returns. These results imply that low-volume tokens' returns respond to

Table 3 Granger causality analysis

Causality directions	Lag	Selection criteria	WALD statistic	*P* value
Leading tokens → follower tokens	4	AIC, H.Q., SC, FPE	8.6	0.07*
Follower tokens → leading tokens	4	AIC, H.Q., SC, FPE	8.8	0.07*
Leading tokens → outlier tokens	4	AIC, H.Q., SC, FPE	0.85	0.93
Outlier tokens → leading tokens	4	AIC, H.Q., SC, FPE	2.3	0.68
Follower tokens → outlier tokens	4	AIC, H.Q., SC, FPE	0.9	0.76
Outlier tokens → follower tokens	4	AIC, H.Q., SC, FPE	0.71	0.95

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$; Selection criteria includes Akaike Information Criterion (AIC), Hannan Quinn (HQ), Schwarz Criterion (Hens and Schenk-Hoppé 2009), and Final Prediction Error (FPE)

Table 4 The results of the augmented VAR test—Eqs. (1) and (2)

Variable	Equation 1	Equation 2
L_{t-1}	0.040134	0.113841*
F_{t-1}	− 0.073763	0.106468
L_{t-2}	0.094056	0.01886
F_{t-2}	0.029343	− 0.04124
L_{t-3}	− 0.023061	0.103661
F_{t-3}	0.050363	0.00862
L_{t-4}	0.098523	0.040011
F_{t-4}	0.121439*	0.231622***
L_{t-5}	− 0.100767	0.015465
F_{t-5}	0.035471	0.042579

***$p < 0.001$; **$p < 0.01$; *$p < 0.05$

the changes in leading tokens' returns. On the other hand, low-volume tokens' returns also exert an impact on leading tokens' returns. Hence, the degree of impact and its directions need further examination through the augmented VAR models. Table 3 also highlights that there is no significant evidence to reject the non-causality hypotheses between Group 1 and Group 3, Group 2 and Group 3. That is, the causal relationships between outliers' returns and the other two groups cannot be observed, which further verifies the outlier cluster membership.

Table 4 shows the results of the augmented VAR Eqs. (1) and (2). It indicates that the followers' returns respond to the changes in the leaders' returns in the same direction with a one-period lag. The return of followers is likewise influenced by its own historical returns with a four-period lag. Meanwhile, changes in the returns of followers cause changes in the leaders' returns with a four-period lag. As a result, Hypothesis 1 is validated. Because high-volume Metaverse tokens respond to market-wise information faster, returns on high-volume Metaverse tokens lead returns on low-volume ones.

In conclusion, this study utilizes spectral clustering techniques to identify a well-balanced grouping of time series data comprising 197 Metaverse tokens, each spanning 365 observations (representing days) per series (Von Luxburg 2007). Through this clustering approach, two distinct clusters, namely the "leading" and "follower" clusters, are determined based on their respective trading volumes. Furthermore, the study confirms the veracity of Hypothesis 1 by establishing a causality relationship between the daily returns of leading Metaverse tokens and those of follower tokens using the VAR (Vector Autoregressive) model.

Discussion

Contributions to knowledge and methodology

One of the paramount concerns of tokenomics among the academic community is understanding how information is transmitted to markets and within the markets, and how markets impound this information into token prices (Cong et al. 2021). Traditional asset-pricing theories imply that knowledge dispersion occurs instantly in a complete and frictionless market (Hens and Schenk-Hoppé 2009). Although this has been demonstrated otherwise in regular financial markets (Hou 2007), there is a lack of empirical evidence to suggest that investors too face significant frictions in the Metaverse token market.

A high trading volume can indicate significant buyer and user interest, while a low trading volume, in comparative terms, can sometimes act as a proxy for insufficient information updating or dissemination (Chae 2005). Market underreaction occurs when investors fail to keep sector-specific public information up to date (Driesprong et al. 2004). Thus momentum effects are expected to occur in low-volume tokens but not in high-volume ones in the intermediate horizon (Lee and Swaminathan 2000). Moreover, the observed causality relationship between the returns of leading and follower tokens indicates the presence of such herding behavior (Spyrou 2013), wherein users tend to imitate the actions of others rather than conducting independent analysis for Metaverse tokens.

This is the first study to document the lead–lag effect of Metaverse tokens. By exploring the interactions between the different clusters of Metaverse tokens, we discover that the returns of each cluster behave differently, which suggests that information can and occasionally does travel slowly within the market. In other words, the leading cluster of tokens could precede the followers, based on the information advantage. Metaverse tokens are distinct from traditional cryptocurrencies like Bitcoin and Ethereum in their broad range of applications such as representing ownership of virtual property, fostering community governance, and empowering creators to monetize their virtual creations, setting them apart from traditional cryptocurrencies mainly used for financial transactions(Cheng et al. 2022). The identification and validation of leading and follower clusters based on trading volumes for Metaverse tokens expands our understanding of how these tokens behave within the virtual world realm, shedding light on their unique dynamics, and potentially contributing to the development of new economic models specific to the metaverse. In a mostly bullish market for Metaverse tokens(Vidal-Tomás 2022), our findings imply that high-volume tokens tend to enjoy earlier sectoral boom because investors keep the information up to date, while the underreaction of lower-volume tokens can be attributed to slower adjustment to market-wide news.

Collectively, the empirical results show that trading volume is a strong predictor of the observed lead–lag patterns in Metaverse crypto tokens. This result is consistent with the differential speed of adjustment hypothesis, i.e. volume-related leadership (Chordia and Swaminathan 2000).

In terms of methodology, the research marks the first attempt to use spectral clustering to model the latent grouping structure of tokens. Spectral clustering, as applied in our research, involves a novel approach to time series clustering by leveraging the spectral decomposition of the affinity matrix. Our findings substantiate that this framework is not only suitable but also highly effective in delineating cluster memberships within the context of tokens or cryptocurrency performance. The clusters derived from our analysis are both theoretically grounded and practically relevant, which open up new avenues for understanding and interpreting complex data structures,

Implications for practitioners

Although the technology is still in its early stages, Metaverse tokens have started to pique the interest of mainstream investors (Vidal-Tomás 2022). Our findings suggest that trade volume contains vital information concerning cross-correlation patterns. Traders could strategically exploit the lead–lag relationship by entering and adjusting positions in follower tokens based on analysis of the leading cluster's market movement. The lead–lag effect could also be integrated into classic alpha strategies to enhance their performance (Criscuolo and Waelbroeck 2012). Therefore, our findings have the potential to enhance trading strategies and returns within the Metaverse token market.

The predictability of Metaverse token returns provides insight into risk propagation and investment market segmentation. By comprehending the grouping structure inherent in Metaverse tokens and the interplay between leading and follower tokens, investors and risk managers can effectively anticipate and manage market risks, and evaluate potential contagion effects and the propagation of risks across diverse clusters of Metaverse tokens. Consequently, this understanding of cluster dynamics empowers investors to make well-informed decisions.

From a managerial standpoint, this research can inform decision-making for businesses operating in the Metaverse ecosystem, helping them better navigate the market, manage risks, and optimize strategies related to Metaverse tokens. It can also aid in the creation of monetization strategies for virtual world developers, offering insights into how to harness the lead–lag effect for their benefit. Venture capitalists (VCs) interested in the Metaverse space can use this information to evaluate potential investment opportunities, assess the growth potential of different tokens, and make more informed decisions regarding funding and partnerships. It underscores the importance of keeping a close watch on the dynamics of Metaverse token clusters to maximize returns and mitigate risks in this emerging and rapidly evolving market.

From the regulators' perspective, our findings imply that herd-like instinct may occur among armature individual investors in the Metaverse token market, where these investors tend to follow what they perceive others to be doing rather than their own analysis. Inadequate individual thought to counteract the other investors' influence in arriving at decisions can expose them to higher risk (Spyrou 2013). A comprehensive understanding of these dynamics can assist regulators and policymakers in formulating appropriate measures to promote market efficiency, safeguard investor interests, and ensure stability within the Metaverse token market. To refrain from sending the herd off the cliff edge, a regulatory regime tailored to the specific characteristics and distinct risks of Metaverse coins should be recommended.

Conclusion and future research

In conclusion, this study utilizes spectral clustering techniques to categorize 197 Metaverse tokens into two clusters based on their trading volumes, confirming a lead–lag relationship between daily returns of leading and follower tokens through a Vector Autoregressive (VAR) model. Traditionally, markets are believed to instantly incorporate information, but our findings suggest potential frictions in Metaverse token markets. Low-volume tokens might exhibit momentum effects due to slower information updates, while high-volume tokens respond faster to marketwide information, showcasing herding behavior among users. This study pioneers documenting lead–lag effects in Metaverse tokens and suggests that information transmission within this market might be gradual, influenced by tokens' unique applications beyond financial transactions. Understanding the leading and follower clusters based on trading volumes aids comprehension of the Metaverse token behavior, potentially contributing to specific economic models for the metaverse.

In addition, trading volume emerges as a strong predictor of lead–lag patterns in Metaverse tokens, aligning with the volume-related leadership hypothesis. Spectral clustering effectively delineates cluster memberships within token performance, offering insights into complex data structures. These findings hold implications for traders, suggesting strategies leveraging the lead–lag relationship for improved performance and risk management. Moreover, they offer insights into risk propagation and market segmentation, empowering investors and risk managers to anticipate and manage risks within diverse token clusters.

For businesses in the Metaverse ecosystem, this research informs decision-making, aiding risk management and strategy optimization concerning Metaverse tokens. Venture capitalists can use these insights to evaluate investment opportunities and growth potential in the Metaverse space. Regulators should take note of potential herd-like behavior among individual investors and consider tailored measures to promote market efficiency, protect investor interests, and ensure stability in the Metaverse token market. Understanding these dynamics can prevent uninformed decisions driven by herd behavior and guide the formulation of a regulatory framework specific to Metaverse tokens.

There are some limitations in this study that we would like to address in future research in this area. Firstly, the data set used in this paper did not document the process of information dissemination and information flow, which could be observed through discussions in major news outlets and forums. If the information dissemination process could be captured and incorporated into future studies, the result may help us better understand how leading and follower tokens respond to information and to what extent the lead–lag exists. On the other hand, the difference in information dissemination may not be an exclusive driving force behind the lead–lag patterns in portfolio returns. For example, the differences in the quality of Metaverse/token-specific news could be another important factor. In future studies, it will be useful to collect data regarding the specific features of each of the Metaverse tokens to identify possible generic trends among the different types of tokens to help us better understand the price determination mechanism for the crypto tokens.

Abbreviations

NFT	Non-fungible tokens
MANA	Decentraland MANA token
Sand	The Sandbox token
KDE	Kernel density estimation
DTW	Dynamic time warping
VAR	Vector autoregression
WEMIX	A blockchain-based global gaming platform developed by wemade tree
AXS	Axie infinity
MST	Minimum spanning tree
ADF	Augmented Dickey–Fuller
KPSS	Kwiatkowski–Phillips–Schmidt–Shin
AIC	Akaike information criterion
HQ	Hannan quinn
FPE	Final prediction error

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