

MODELING CYCLICAL PATTERNS IN THE CRYPTOCURRENCY MARKET

The cryptocurrency market is characterized by high volatility, rapidly shifting trends, and a significant influence of behavioral factors, which complicates price forecasting and risk assessment. The dynamics of leading assets, such as Bitcoin and Ethereum, largely determine overall market trends. At the same time, empirical observations indicate the presence of recurring phases of development, suggesting the existence of cyclical patterns that are important for both theoretical analysis and investment decisions.

Research on the cyclical nature of financial markets is based on classical theories of economic cycles and modern methods of time series analysis. The scientific literature highlights the high volatility of cryptocurrencies and their unstable dynamics [1], and examines Bitcoin as a new asset class and its relationship with traditional financial instruments [2]. Separately, the role of fundamental factors is investigated, in particular Bitcoin halving as a driver of long-term fluctuations [3], as well as the application of spectral analysis and data processing methods to identify hidden cycles [4; 5].

From the perspective of modern financial theory, the cyclical nature of cryptocurrency markets can be viewed as a specific manifestation of the general patterns of financial cycles, known as stylized facts. Similar to traditional financial instruments, cryptocurrencies exhibit volatility clustering, asymmetry in the distribution of returns, as well as the presence of “overheating” and correction phases, which is consistent with the results of econometric analysis of financial time series.

At the same time, the absence of classical fundamental drivers, such as monetary policy or corporate indicators, complicates the specification of econometric models and reduces their explanatory power. This necessitates the use of more flexible approaches, in particular time series models, spectral analysis, and volatility analysis. Under such conditions, econometric tools serve as a key means of identifying cyclical patterns [1].

To identify cyclical patterns in cryptocurrency dynamics, a set of time series analysis methods is applied. The basic approach is series decomposition:

$$y_t = \tau_t + c_t \quad (1)$$

where y_t — the price of the cryptocurrency, τ_t — the trend, c_t — the cyclical component. This decomposition allows us to separate the long-term market trend from short- and medium-term fluctuations, which is critical for the accurate identification of cycles. In practice, smoothing filters can be used to estimate the trend component, specifically moving averages or the Hodrick–Prescott filter, which allows us to identify the underlying structure of the dynamics.

To analyze periodicity, the following spectral representation is most commonly used:

$$\sum_{k=1}^n A_k \cos(\omega_k t) + B_k \sin(\omega_k t) \quad (2)$$

where ω_k — frequencies of harmonics characterizing the periodicity of oscillations, and the coefficients A_k та B_k their amplitudes. The application of spectral analysis allows us to identify dominant cycles in a time series and estimate their duration, which is particularly important for the study of cryptocurrencies, where cyclical nature can be both regular and quasi-periodic in nature.

Additionally, autocorrelation analysis (ACF and PACF) is used to identify relationships between current and lagged values in the series and to estimate the duration of cycles. Significant autocorrelations at specific lags indicate the presence of cyclical components and are used to specify econometric models.

Modern approaches to identifying cyclical patterns in financial time series significantly expand the classical econometric toolkit. In particular, methods of spectral-temporal analysis, such as the wavelet transform, are increasingly being used to investigate the variability of cycles over time and identify local periodicities. Conditional heteroscedasticity models (ARCH/GARCH) also play an important role, as they enable the analysis of volatility dynamics and its cyclical properties. In addition, machine learning methods are used, specifically recurrent neural networks and clustering algorithms, which allow for the detection of complex nonlinear dependencies and hidden patterns in large datasets. The application of such approaches is particularly relevant for cryptocurrency markets, where traditional models are often unable to fully account for the instability and nonlinearity of the dynamics.

The results of the analysis indicate the presence of multi-level cyclicity in cryptocurrency dynamics. For Bitcoin, a long-term cycle lasting approximately 3–4 years (on average about 1,400 days) can be observed, which aligns with the halving cycle [3]. In particular, the intervals between halving events in 2012, 2016, 2020, and 2024 were approximately 1,319, 1,402, and 1,440 days, respectively, confirming the relative regularity of long-term fluctuations. Following each such reward halving, a price growth phase is observed, which typically lasts from several months to a year and is accompanied by increased market activity. The subsequent correction phase is characterized by falling prices and a gradual decline in trading volumes.

An analysis of logarithmic returns shows that during growth phases, there is not only an increase in average returns but also a significant rise in their variation, indicating a volatility clustering effect. In downturn phases, conversely, returns exhibit a more asymmetric distribution with a predominance of negative values and a decrease in the intensity of fluctuations. Additionally, it has been established that the midpoint of the cycle (defined as the time interval between halvings) does not always coincide with the moment when the median level of prices or returns is reached, indicating the asymmetry of cyclical dynamics and the uneven distribution of market activity within the period. Estimates of the standard deviation of log-returns in growth phases exceed the corresponding values in decline phases, which further confirms the asymmetry of market dynamics. The results obtained are consistent with the hypothesis regarding the nonlinear nature of cryptocurrency markets and confirm the appropriateness of using econometric methods of time series analysis for their study.

Short-term cyclical fluctuations in the cryptocurrency market are driven by a variety of factors, among which market sentiment, news shocks, and speculative activity play a key role. Unlike long-term trends, such fluctuations are irregular in nature and often arise in response to news, changes in the regulatory environment, technological updates, or sudden shifts in liquidity. Empirical analysis of logarithmic returns shows that short-term phases are accompanied by increased volatility and clustering effects, indicating the presence of local cycles of varying duration and intensity. At the same time, such cycles do not always align with fundamental events, confirming the dominance of behavioral factors in short-term dynamics. Thus, the cryptocurrency market combines fundamental (exogenous) and behavioral (endogenous) sources of cyclicity, which form its complex nonlinear structure.

Conclusions. The present study confirms the existence of pronounced cyclical patterns in the dynamics of cryptocurrencies, which manifest themselves in both long-term and short-term time horizons. The use of econometric methods for time series analysis, in particular decomposition, spectral, and autocorrelation analysis, allows us to identify different types of cycles, assess their duration and structure, and improve the quality of market process interpretation. It has been established that fundamental mechanisms, primarily Bitcoin halving, act as the key driver of long-term fluctuations, while short-term dynamics are determined primarily by behavioral factors and information impulses. Additionally, the asymmetry of cycles and the uneven distribution of returns within periods were identified, confirming the nonlinear nature of cryptocurrency markets. In this context, a promising direction for further research is the integration of classical econometric approaches with modern data analysis methods, particularly machine learning algorithms, which will allow the cyclical dynamics of cryptocurrencies to be considered as an independent modeling object. Such an approach will facilitate a more accurate identification of cycle parameters, their duration, amplitude, and phase structure, and will also allow for accounting for their variability over time. This,

in turn, will provide a deeper understanding of the mechanisms underlying cyclical fluctuations and enhance the effectiveness of analytical and predictive models.

References

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SYSTEM OF STATISTICAL INDICATORS OF THE INTELLECTUAL PROPERTY MARKET IN UKRAINE.

The entry of human civilization into the era of post-industrial economic development is accompanied by a transformation of society's priorities, a change in the structure of production, and the application of new information technologies. Information and services acquire a higher market value, which gradually leads to a decrease in the role of material assets as a source of competitive advantage. The stages of formation of the intellectual property institute in Ukraine have become typical for many European countries. However, the process of formation was very slow, but Ukraine's entry into the international economic space accelerated these processes. The development of the domestic intellectual property market in our country is accompanied by the emergence of many problems of this market segment of our country.

To form a sustainable demand for intellectual products, it is necessary to create conditions for stimulating the development of intellectual activity and market relations in this area, to statistically assess the state and prospects for the development of processes occurring in the studied market. In the context of society's transition to a market economy, the assessment and analysis of processes occurring in the intellectual property market form new requirements for the completeness of the information base, the choice of indicators, techniques and methods for building models, and the assessment of the reliability and validity of the forecasts obtained.

The analysis made it possible to identify the following groups of intellectual property market entities:

- producers of intellectual property objects;
- consumers of intellectual property objects;
- intermediaries in transactions with intellectual property objects.

It should be noted that each of the identified groups is characterized by a mobile and variable structure.

When conducting economic and statistical analysis and forecasting the development of the intellectual property market, one should take into account both its qualitative content and quantitative form of expression.