

Application of Predictive Models in Bitcoin Forecasting and Risk Management

Beata Butryn

Wrocław University of Economics and Business

e-mail: beata.butryn@ue.wroc.pl

ORCID: [0000-0003-4992-3044](https://orcid.org/0000-0003-4992-3044)

Kamil Lupa

Wrocław University of Economics and Business

e-mail: lupakamil@o2.pl

ORCID: [0009-0001-0658-0427](https://orcid.org/0009-0001-0658-0427)

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Abstract

Aim: The aim of the article was to assess the statistical relevance of the Stock-to-Flow (S2F) model in forecasting the value of Bitcoin by 2030 and its usefulness in risk management.

Methodology: A method based on quantitative analysis of the Stock-to-Flow (S2F) model was used. Bitcoin price data and the corresponding S2F values between 2009 and 2025 were collected, formatted and cleaned of redundant information. Then a predictive model in the form of logarithmic-linear regression was defined. In the next step, a statistical price was made of the degree of matching the model with the data. Finally, specific forecast values were determined and potential turning points in price cycles were identified.

Results: The results of quantitative analysis based on the Stock-to-Flow (S2F) model indicate a strong statistical relationship between Bitcoin's rarity and its market price over the period under review. The S2F model, despite its limitations considering only the supply side, apart from rapid changes on the demand side, showed a high predictive capacity for medium-term trends and allowed for the identification of market phases, making it a useful instrument in the process of reducing investment risk.

Implications and recommendations: The stock-to-flow model is a tool to help assess Bitcoin's long-term supply dynamics and the role of halving cycles as a deflationary mechanism. In the context of risk management in financial markets it offers a useful timeframe to identify cyclical patterns and support allocation decisions over a multi-year horizon. To increase the effectiveness of risk management it should be a hybrid element with other on-chain metrics (e.g. the number of new network users, their purchase price) or risk measures such as Value at Risk (VaR).

Originality/value: The use of cryptocurrencies and predictive models in risk management in financial markets has shown measurable benefits resulting from their use. The potential of medium-term models to predict future values and assess their usefulness in an effective investment risk management strategy in the maturing cryptocurrency market was estimated.

Keywords: predictive model, Stock-to-Flow (S2F) model, Bitcoin

1. Introduction

Contemporary financial markets, and particularly the emerging sector of cryptocurrencies, are characterised by exceptional volatility, and this necessitates the implementation of advanced analytical tools to assess and mitigate investment risk. The use of classical analytical methods is now becoming insufficient, hence modern machine learning algorithms have found their application. A key issue addressed in the analyses was the specific cyclical and nonlinearity of the cryptocurrency market, which differs significantly from traditional business cycles. As indicated by M'bakob (2024) and Kyriazis (2020), this market operates in repetitive phases determined by various technological factors. Such factors include halving cycles that limit asset supply, as well as behavioural factors manifested through herd behaviour among retail investors and sudden shifts in market sentiment. Understanding these mechanisms is essential for the appropriate calibration of predictive models. The aim of the study was to assess the statistical significance of the Stock-to-Flow (S2F) model in forecasting the value of Bitcoin up to the year 2030 and its usefulness in risk management. The conducted study sought to answer the question: to what extent does a logarithmic-linear regression based on asset scarcity allow for reliably identifying price maxima and minima through to 2030? In response to this question, the following hypothesis was formulated: the S2F model demonstrates predictive capability for medium-term trends, serving as an effective tool in investment risk management through the precise mapping of market phases.

2. Literature Review

2.1. Characteristics of the Cryptocurrency Market in the Context of Predictive Modelling

The dynamic development of blockchain technology, which serves as a decentralised and immutable transaction ledger, has significantly influenced the transparency and auditability of financial flows (Nakamoto, 2008). However, from the standpoint of predictive modelling, this market exhibits unique features that pose challenges to researchers. As Zahid et al. (2022) argued, the high volatility and nonlinear nature of cryptocurrency price changes mean that traditional, linear statistical models often provide inaccurate forecasts. The authors stated that these markets are too complex and highly dynamic, thus requiring the use of advanced deep learning algorithms capable of capturing intricate dependencies in time series data.

A significant characteristic of this sector is that asset valuation is not based on classic economic fundamentals as is the case in traditional markets. According to studies cited by Changchit et al. (2025), the key determinants of cryptocurrency prices are technological factors and the intensity of media

coverage. This leads to a strong asymmetry of information in which individual investors react to informational noise, generating sudden shifts in liquidity and volatility not observed in traditional markets (cf. Lee & Jeong, 2023). Integrating crypto-asset infrastructures such as blockchain with predictive models enables the creation of risk management systems based on real-time data. The use of artificial intelligence not only allows for the identification of threats but also supports the optimisation of investment portfolios under conditions of extreme market uncertainty (cf. Bergsli et al., 2022; Shahbazi & Byun, 2022). It is important for modern predictive approaches to adapt to the dynamic structure of the market, capturing behavioural variables and current social sentiment which are the main components of price cycles in this sector (Kyriazis, 2020).

2.2. Classic and Contemporary Predictive Models

Over time the tools used for predictive modelling have evolved greatly. Initially, investors wishing to minimise investment risk used classic models based on historical data, but later these models have been integrated with artificial intelligence technology to capture more dependencies and respond to certain events in real time.

Classic models are characterised by relatively easy implementation and high interpretability. Their main task is to identify market trends and volatility based on the assumption of stationarity in market processes. The most important of these are listed in Table 1.

Table 1. Classic predictive models

Model	Description	Formula (Mathematical Scheme)
Linear Regression	A model describing a linear relationship between a dependent variable and independent variables	$y_t = \beta_0 + \beta_1 x_t + \varepsilon_t$
ARIMA (AutoRegressive Integrated Moving Average)	A time series model that combines autoregression with differencing and a moving average	$\phi(B)(1 - B)^d y_t = \theta(B)\varepsilon_t$
GARCH (Generalised Autoregressive Conditional Heteroskedasticity)	A model used for estimating volatility in time series	$\sigma_t^2 = \alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$
Holt–Winters Method	An exponential smoothing method that accounts for trend and seasonality	$\{y\}_{t+h} = (l_t + h b_t) + s_{\{t-m+h \bmod m\}} \{(\text{additive version})\}$

Source: own elaboration based on (Box et al., 2015).

The above classical models are highly effective in stable market conditions. However, as Katsiampa (2017) pointed out, in the case of assets with extreme volatility, such as cryptocurrencies, classical linear models often fail to keep up with the rapid structural changes occurring in the market. When historical data exhibit high complexity or are irregular, the literature indicates the superiority of machine learning models which are capable of detecting hidden patterns and nonlinear relationships within the data.

Of all the models presented in Table 2, the LSTM (Long Short-Term Memory) models are of particular significance. Thanks to their architecture they can ‘remember’ important events from the past. This is crucial when analysing halving cycles and long-term behavioural trends (Dixon et al., 2020).

Table 2. Machine learning models in stock market applications

Model	Description Tailored to Market Applications	Application
RandomForest	Creates decision trees on random data subsets; robust to market noise and volatility	Credit risk assessment, market anomaly detection
SupportVectorMachines (SVM)	Establishes a decision boundary to separate data classes – e.g. safe vs risky investments	Asset classification, market event recognition, trend prediction
DeepNeural Networks (DNN)	Learns complex, non-linear relationships between financial variables and market behaviour	Stock price forecasting, predicting market reactions to information, risk scoring
LSTM (Long Short-Term Memory)	Analyses historical financial data by accounting for temporal dependencies, including long-term horizons	Market volatility forecasting, stock price prediction, buy/sell signals

Source: own elaboration based on (Dixon et al., 2020).

Modern predictive systems are often integrated with risk measures. Such integration allows for the creation of scenarios of potential losses and supports decision-making on stock exchanges. The most commonly used measures are presented in Table 3.

Table 3. Risk measures in investment management

Model/ Measure	Description	Application in Stock Market Risk Management
Value atRisk (VaR)	A statistical measure that determines the maximum expected portfolio loss over a given time horizon at a specific confidence level	Used to establish portfolio risk limits and for regulatory risk reporting
Conditional Value at Risk (CVaR)	An extension of VaR that accounts for the average loss in cases where the VaR threshold is exceeded	Allows for a more accurate assessment of tail risk (extreme market events), such as sharp index declines most frequently occurring during crises or geopolitical escalations

Source: own elaboration based on (Hull, 2023).

For predictive models to operate effectively, high-quality data is essential. In the context of blockchain technology this significance is amplified by its transparency and immutability (Nakamoto, 2008). The utilisation of blockchain technology enhances the resilience of systems against unpredictable market volatility, prevents data manipulation and improves the quality of business decisions under conditions of high market uncertainty.

2.3. Examples of Using Predictive Models for Cryptocurrency Valuation

Attempts to define the objective value of digital assets have developed two parallel research streams. The first is the fundamental trend, i.e. one based on the scarcity of a resource, and the second is the technical current, which uses advanced data analytics. The Stock-to-Flow (S2F) model, popularised by analyst PlanB (2019), occupies a central place in the Bitcoin valuation debate. The construction of this model is based on the assumption that the scarcity of an asset, defined as the ratio of existing resources to the current annual supply, is the main determinant of the growth of its capital value. Although this model is derived from the analyses of market practitioners, it quickly became the subject of academic verification. Key evidence in this regard was provided by Kristoufek (2015), whose cointegration tests confirmed the existence of a long-term statistical relationship between the rarity parameter of an asset and the market price, who suggested that Bitcoin's characteristics show

significant similarities to precious metals, which justifies the use of supply-flow models in the process of estimating its future value.

However, it should be noted that the modern methodology of cryptocurrency valuation is not limited to supply mechanisms. The literature on operational technologies based on deep learning is gaining increasing importance. As Omole and Enke (2024) proved, the use of hybrid neural networks, connecting convolutional layers (CNNs) with LSTM modules, allows for the identification of nonlinear correlations. This is important because these correlations remain invisible for classic models. The high effectiveness of these solutions, often exceeding the threshold of 80% prediction accuracy, indicates the growing ability of algorithms to interpret market sentiment and complex capital flows, which confirms their use in risk management models.

An important complement to this perspective is the academic literature on the S2F model, which highlights its growing popularity as a valuation framework for Bitcoin (Morillon & Chacon, 2022). The model is often discussed in the context of market expectations and cyclical dynamics, particularly during periods associated with halving events. Kristoufek (2015) expanded this perspective, postulating an integrated approach in which hard scarcity data is corrected by dynamic trend analysis. In turn, Wątopek et al. (2021) proved that as the Bitcoin market reaches maturity, predictive models must be increasingly calibrated with macroeconomic variables. Modern cryptocurrency valuation is based on a kind of duality. On the one hand, it is based on mathematical supply correlation (S2F), and on the other hand, on adaptive algorithmic intelligence (AI). This synergy allows for the construction of a comprehensive framework of modern financial engineering, capable of describing the specifics of digital assets.

3. Methodology

The study aimed to analyse and forecast the value of Bitcoin in the medium term (until 2030). The analysis made it possible to estimate the potential of medium-term models to predict future values and assess their usefulness in an effective investment risk management process. The research procedures undertaken were of a quantitative nature, which allowed for the objective verification of the hypotheses.

The research was based on the quantitative analysis of the Stock-to-Flow (S2F) model and consisted of five stages. The choice of this method was justified by Bitcoin's unique supply structure, the scarcity of which can be precisely described mathematically, making the S2F model an adequate tool for analysing its market value. This approach provided a comprehensive solution to the problem and the reliability of the results obtained. The study was divided into the following stages:

1. Collecting historical data on the price of Bitcoin and the corresponding values of the S2F indicator between 2010 and 2025.
2. Formatting and cleaning up a dataset of redundant information.
3. Defining a predictive model in the form of logarithmic-linear regression, in which the dependent variable is the logarithm of the price and the independent variable is the logarithm of the S2F coefficient.
4. Conducting statistical evaluation of the degree of adaptation of the model to historical data.
5. Determining specific forecast values and identification of potential turning points in price cycles.
6. Conducting out-of-sample validation used a training period (July 2010 – July 2022, $n = 25$) and a holdout period (January 2023 – July 2025, $n = 6$), which was not used for model calibration.

The regression model took the form of:

$$\log P(t) = \alpha \cdot \log(S(t)) + \beta, \quad (1)$$

where: $P(t)$ – Bitcoin price at time t , $S(t)$ – stock-to-flow indicator at time t , α , β – empirically adjusted regression parameters.

The model was calibrated on a dataset of $n = 31$ semi-annual price and S2F observations spanning July 2010 to July 2025, with Table 4 below presenting a subset of these observations corresponding to halving reference dates. The least-squares fit yielded $\alpha = 2.906$ ($SE = 0.154$, $t = 18.85$, $p < 0.001$, 95% CI : 2.591-3.221) and $\beta = -1.530$ ($SE = 0.497$, $t = -3.08$, $p = 0.004$, 95% CI : -2.545 to -0.514). Representative observations include: \$0.09 at S2F = 1.53 (July 2010), \$13,657.20 at S2F = 25.51 (January 2018), \$47,686.81 at S2F = 57.60 (January 2022), and \$105,698.28 at S2F = 121.06 (July 2025). To assess whether the fit reflected a genuine long-run relationship rather than a spurious trend, Augmented Dickey-Fuller and Engle-Granger cointegration tests were additionally conducted on the log-price and log-S2F series. The results did not provide statistically significant evidence of cointegration ($p = 0.285$), indicating that the strength of the model fit should be interpreted with caution and did not, in itself, establish beyond doubt the existence of a causal mechanism between scarcity and price.

The model inputs included:

- a list of dates,
- historical values of the BTC exchange rate,
- planned halving dates.

The evaluation of the model's fit with historical data was determined by the coefficient of determination R^2 . The last stage was a multi-variant price forecast until 2030 and the interpretation of the results. The different variants of the forecast were equivalent to the aggressive, average, moderate and conservative approaches. The model was based on the assumption that Bitcoin's price is a function of its scarcity, defined as the ratio of resources (stock) to the ratio of annual production of new units (flow). This approach verified the hypothesis of the determining influence of halving cycles on Bitcoin's valuation.

To determine the values of deviations between the predicted and actual exchange rates, the following statistical error measures were used:

$$MAE = \left(\frac{1}{n}\right) \sum_{i=1}^n |y_i - \hat{y}_i|, \quad (2)$$

and

$$RMSE = \sqrt{\left[\left(\frac{1}{n}\right) \sum_{i=1}^n |y_i - \hat{y}_i|^2\right]}, \quad (3)$$

where: y_i – the actual value of the price, $\hat{y}_i$ – the value predicted by the model, n – the number of observations.

The RMSE (Root Mean Squared Error) indicator was strongly justified in the analysis of high-volatility assets, as by raising the error value squared it more strongly exposed larger forecast deviations. This allowed for a better assessment of the risk of error during periods of rapid market volatility. Such indicators were the foundation for the forecasting model.

To empirically assess downside risk rather than solely in conceptual terms, the VaR and CVaR measures were calculated, based on semi-annual returns. Due to the high volatility of Bitcoin prices in the early period of its existence, the historical method was used instead of an approach assuming a normal distribution of returns.

$$VaR_{\alpha(R)} = -Q_{\alpha(R)}, \quad (4)$$

and

$$CVaR_{\alpha(R)} = -E[R \mid R \leq Q_{\alpha(R)}], \quad (5)$$

where: R – semi-annual logarithmic rate of return, α – confidence level (two levels were adopted: 0.95% and 0.99%), $Q_{\alpha}(R)$ – the α th quantile of the return distribution, $E[R | R \leq Q_{\alpha}(R)]$ – the average return within the tail at or below the quantile.

4. Results

During the calibration of the model based on historical data, a regression line characterised by the high level of matching to the empirical data was established. The collected data, such as exchange rate data and the Stock-to-Flow ratio, is presented in the table below.

Table 4. Historical data on prices and s2f at halving dates

Year	Price (USD)	S2F
2009-01-03	0.05	1.2
2010-07-17	0.08	1.5
2012-11-28	12.35	3.8
2016-07-09	650.54	25.0
2020-05-11	8,500.00	56.2
2024-04-20	73,750.07	120.5

Source: In-house elaboration based on TradingView historical data.

The coefficient of determination R^2 reached 0.925, which meant that the S2F model explained 92.5% of the variance in Bitcoin's log-transformed price series. Such a high result clearly indicated a strong correlation between the rarity of an asset and its market valuation. In response to the research question, this level of statistical fit suggested that the logarithmic-linear regression model may serve as a useful tool for mapping trends in the medium and long term. At the same time, a high R^2 value alone does not demonstrate the predictive accuracy of the model or establish a causal relationship between scarcity and price. To calculate potential forecast errors, the mean absolute error (MAE) = \$18,515.66 and the root of the mean squared error (RMSE) = \$48,731.26 were calculated. A significantly higher RMSE error value indicates the periodic occurrence of sharp deviations from theoretical values. This is due to the relatively young and not yet fully regulated crypto-asset market, which is highly susceptible to any geopolitical or manipulative events. An integral part of the results was a multi-variant long-term forecast until 2030, the course of which is shown Figure 1.

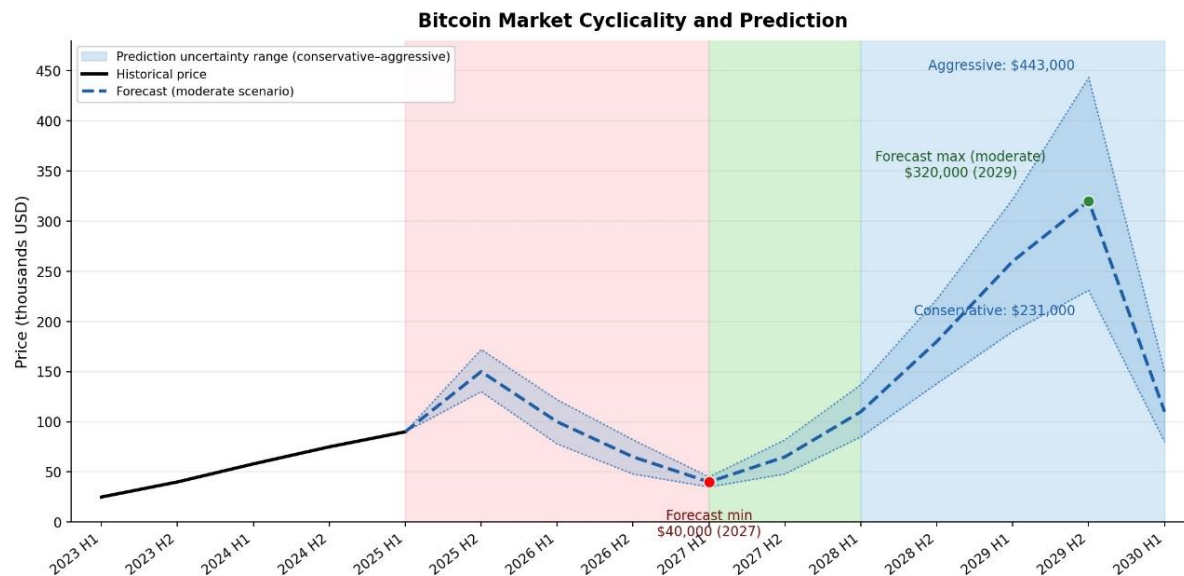


Fig. 1. Bitcoin Market Cyclicity and Prediction

Source: own study based on TradingView historical data.

To assess the robustness of the model the regression was re-estimated on the training sample covering the period from July 2010 to July 2022 ($n = 25$), yielding $\alpha = 3.147$ and $\beta = -2.030$, consistent with the full-sample results. The model was then applied to six out-of-sample observations (January 2023 – July 2025). The out-of-sample error amounted to $MAE = \$198,290.34$ and $RMSE = \$267,618.42$, substantially higher in-sample. For observations within the range of the training data ($S2F \approx 58.6-59.6$), the error remained relatively low ($MAE = \$18,961.01$). In contrast, for observations outside this range ($S2F \approx 120.1-121.1$), the error increased significantly ($MAE = \$377,619.67$). These results suggest that the decline in model accuracy may be associated with extrapolation beyond the range of $S2F$ values observed in the training sample, driven by stepwise $S2F$ changes after halving. However, this does not imply a general failure of the model, but rather highlights the limitations in its applicability outside the estimation sample.

The scenario analysis indicated different paths of market development depending on the dynamics of adoption and regulation. Figure 1 presents several scenarios. The predictive model points to reaching the next high around 2029 and a potential low in 2027, in line with the confirmation of the thesis that halving makes a significant impact on the price of Bitcoin.

For transparency and reproducibility, the specific point forecasts were obtained through a cycle-multiplier extrapolation rather than a direct extrapolation of the calibrated regression line. The ratio between each successive halving-cycle price peak was calculated (Nov 2013: \$1,127; Dec 2017: \$19,665; Nov 2021: \$69,044; Oct 2025: \$126,198), yielding peak-to-peak multipliers of 17.45, 3.51 and 1.83. Consistent with the documented pattern of diminishing cycle amplitude as the market matures, the geometric mean of the two most recent multipliers, $\sqrt{3.51 \times 1.83} = 2.53$, was applied to the current cycle peak to project the moderate scenario for the 2029 cycle top ($\approx \$320,000$). An analogous calculation, based on the retention fraction between each cycle's peak and its subsequent bear-market trough (Jan 2015: \$152; Dec 2018: \$3,200; Nov 2022: \$15,500), was used to project the 2027 cyclical low ($\approx \$37,000 - \$40,000$). As these bounds rest on only three completed halving-cycle multipliers, constructing a formal statistical confidence interval (e.g. via bootstrap resampling or Monte Carlo simulation) would imply a degree of statistical precision that such a small sample cannot support. Instead, the upper and lower bounds of the 2029 forecast were obtained as a scenario-based sensitivity range: the largest and smallest of the two most recent peak-to-peak multipliers (3.51 and 1.83) were applied directly to the current cycle peak, rather than only their geometric mean, yielding

an aggressive bound of $\approx \$443,000$ ($\$126,198 \times 3.51$) and a conservative bound of $\approx \$231,000$ ($\$126,198 \times 1.83$). This approach followed directly from the multiplier framework already used for the moderate scenario, offered as a sensitivity analysis around the point forecast rather than a probabilistic confidence interval, given the limited number of completed cycles available for estimation.

According to the model, the local minimum after the distribution phase will be reached in mid-2027 at \$40,000. Once this level is reached, the market will be in an accumulation phase in anticipation of the next halving in 2028, followed by a bull market phase. The moderate scenario (represented by the averaged path) predicts reaching a peak of the cycle at \$320,000 in 2029. This variant assumes stable growth within the designated regression channel. The upper border of the band (Uncertainty Band) depicts an aggressive scenario approaching \$443,000 at the peak of the bull market. The conservative variant, on the other hand, sets the lower bound of the expected increases at around \$231,000.

The above results allow for positive verification of the hypothesis: the S2F model showed a high predictive ability for medium-term trends, allowing for the identification of market phases, which makes it a useful instrument in the process of reducing investment risk. However, it is worth pointing out some limitations of this study. The Stock-to-Flow model was based solely on the supply side (scarcity), ignoring rapid changes on the demand side. These factors can be triggered by macroeconomic or regulatory changes. In addition, the progressive institutionalisation of the Bitcoin market may lead to a 'smoothing' of halving cycles in the future, which will reduce the relevance of historical correlations in the coming years. Beyond these structural limitations the S2F model has also been the subject of considerable academic and practitioner debate regarding its statistical robustness and practical usefulness. For instance, Morillon and Chacon (2022) found that while the model's fit is not highly sensitive to specific parameter assumptions, a dynamic trading strategy built on its deviation signals substantially underperforms a simple buy-and-hold approach, indicating that a strong statistical fit does not necessarily translate into superior investment performance. This distinction between explanatory fit and practical trading value is an important caveat for interpreting the presented results.

This study focuses on the analysis of the Stock-to-Flow model as a tool for forecasting the price of Bitcoin and assessing investment risk. Consequently, it did not include a direct empirical comparison with ARIMA, GARCH or LSTM models. The S2F model represents a fundamentally different modelling approach from the aforementioned statistical and algorithmic models, being based on a scarcity mechanism linked to the halving schedule. In contrast, ARIMA, GARCH and LSTM are statistical or algorithmic models fitted to patterns observed in historical data without relying on an underlying economic mechanism of price formation. Omole and Enke (2024) reported that hybrid CNN–LSTM architectures achieved directional prediction accuracy exceeding 80%. This suggests superior point forecasting performance, albeit at the expense of interpretability and without providing a causal explanation for price movements. Similarly, Katsiampa (2017) noted that classical volatility models, e.g. GARCH, struggle to capture the structural breaks characteristic of highly volatile assets such as cryptocurrencies. A meaningful comparison between these approaches and the S2F model would require a common validation framework, including identical training and testing periods and the same error metrics. Building directly on the expanded $n = 31$ dataset introduced in this study, such a comparison is proposed as a natural direction for future empirical research.

5. Discussion and Conclusions

The results confirmed a strong statistical relationship between Bitcoin's rarity and its market price, and demonstrated the role of halving-driven scarcity in shaping the asset's deflationary character. In the context of risk management, identifying cyclical market phases makes it easier to construct hedging strategies, portfolio allocation, and exposure limits on risky assets. This approach is part of a broader trend of using predictive models to improve risk management processes. At the same time, the obtained measures of forecasting errors revealed significant periodic deviations of the model from the

actual quotations. These deviations occurred primarily in phases of rapid market movements, both during bull markets (with market overheating and euphoric effect) and a bear market (when there is above-average market fear). This is influenced by risk determinants such as:

- changes in the global macroeconomic environment (interest rate level or correlation with other assets),
- progressive adoption of the cryptocurrency market (inflow of capital through ETFs, corporate strategies, legal regulations),
- external manipulative factors or speculative behaviour characteristic of the young market.

To move beyond a purely conceptual treatment of risk, VaR and CVaR were empirically calculated based on semi-annual logarithmic returns ($n = 30$, historical method): 95% VaR = 56.7%, 95% CvaR = 62.7%, 99% VaR = 63.9%, and 99% CVaR = 65.7%. The parametric estimate produced implausible values (95% VaR > 1000%) due to the skewness of the distribution in the 2011 period, which confirms the appropriateness of the historical method. The two worst semi-annual periods (−65.7% and −59.6%) occurred immediately after cycle peaks, corroborating the risk determinants discussed above. With $n = 30$, the 95%/99% tail estimates were based on 2 and 1 observations respectively, therefore the results should be interpreted as an illustration of risk magnitude rather than a precise estimator. Additionally, the semi-annual horizon deviated from standard VaR practice, and the sample covered the pre-institutionalisation period (2010-2012), limiting comparability with Bitcoin's current risk profile. A formal backtest quantifying the extent to which S2F-informed signals would have improved the realised portfolio performance relative to a static allocation fell outside the scope of this study and is proposed as a direction for future empirical research.

Confirmation of these observations is provided by Shelton (2024) in a study on Bitcoin return prediction, stating that the stock-to-flow model explains historical returns in the calibration sample well, but has a limited ability to forecast Bitcoin returns outside of the calibration sample. The author emphasised that the model focuses on predicting the price level and not directly on the rate of return, which limits its forecasting usefulness beyond historical data. This factor directly affects risk management processes where reliable out-of-sample forecasts are crucial for assessing tail risk and building investment portfolios.

The predictive model until 2030 provided a useful range of possible scenarios for market development in the perspective of risk management. The forecast set a market low in the distribution and accumulation phase around mid-2027, followed by another halving in 2028, with a growth phase leading to the peak of the cycle in 2029. The upper limit of the aggressive scenario assumed strong institutional demand and positive regulatory impulses, which translates into the occurrence of stock market euphoria. The lower end of the conservative scenario took into account the risk, tightening of the regulatory framework or increased competition from other digital assets, which would result in the dilution of market capital. Such a structure consistently confirmed the cyclical nature of the Bitcoin market, in which halving plays the supply mechanism, and thus periods of variable risk. One should emphasise the fundamental limitations of the S2F model as a tool supporting risk management in the conditions of an increasingly mature cryptocurrency market. With the increase in market capitalisation and the entry of institutional investors, the importance of supply mechanics decreases in favour of demand factors, such as network adoption or utility as a reserve of value for states. The model assumed a relatively constant relationship between scarcity and price, while Bitcoin's actual valuation is subject to increasingly strong external and macroeconomic influences, which lowers the ability to predict risk in the short and medium term.

The S2F model helps with assessing Bitcoin's long-term supply dynamics and supports allocation decisions over a multi-year horizon. Given its limitations beyond the calibration sample, it should function as a hybrid element alongside other on-chain metrics or risk measures such as VaR, rather than as a standalone forecasting tool.

References

- Bergsli, L. Ø., Lind, A. F., Molnár, P., & Polasik, M. (2022). Forecasting Volatility of Bitcoin. *Research in International Business and Finance*, 59, 101540. <https://doi.org/10.1016/j.ribaf.2021.101540>
- Box, G. E. P., Jenkins, G. M., Reinsel, G. C., & Ljung, G. M. (2015). *Time Series Analysis: Forecasting and Control* (5th ed.). Wiley.
- Changchit, C., Cutshall, R., Pham, L., & Bland, E. (2025). Psychological and Technological Factors Shaping Cryptocurrency Investment: The Moderating Role of Personality Traits. *Acta Psychologica*, 260, 105606. <https://doi.org/10.1016/j.actpsy.2025.105606>
- Dixon, M. F., Halperin, I., & Bilokon, P. (2020). *Machine Learning in Finance: From Theory to Practice*. Springer. <https://doi.org/10.1007/978-3-030-41068-1>
- Hull, J. C. (2023). *Risk Management and Financial Institutions* (6th ed.). Wiley.
- Katsiampa, P. (2017). Volatility Estimation for Bitcoin: A Comparison of GARCH Models. *Economics Letters*, 158, 3-6. <https://doi.org/10.1016/j.econlet.2017.06.023>
- Kristoufek, L. (2015). What Are the Main Drivers of the Bitcoin Price? Evidence from Wavelet Coherence Analysis. *PLOS ONE*, 10(4), E0123923. <https://doi.org/10.1371/journal.pone.0123923>
- Kyriazis, N. A. (2020). Herding Behaviour in Digital Currency Markets: An Integrated Survey and Empirical Estimation. *Heliyon*, 6(8), e04752. <https://doi.org/10.1016/j.heliyon.2020.e04752>
- Lee, K., & Jeong, D. (2023). Too Much Is Too Bad: The Effect of Media Coverage on the Price Volatility of Cryptocurrencies. *Journal of International Money and Finance*, 133, 102823. <https://doi.org/10.1016/j.jimonfin.2023.102823>
- M'bakob, G. B. (2024). Bubbles in Bitcoin and Ethereum: The Role of Halving in the Formation of Super Cycles. *Sustainable Futures*, 7, 100178. <https://doi.org/10.1016/j.sfr.2024.100178>
- Morillon, T. G., & Chacon, R. G. (2022). Dissecting the Stock-to-Flow Model for Bitcoin. *Studies in Economics and Finance*, 39(3), 506-523. <https://doi.org/10.1108/SEF-10-2021-0409>
- Nakamoto, S. (2008). *Bitcoin: A Peer-to-Peer Electronic Cash System*. Bitcoin. Retrieved August 31, 2026, from <https://bitcoin.org/bitcoin.pdf>
- Omole, O., & Enke, D. (2024). Deep Learning for Bitcoin Price Direction Prediction: Models and Trading Strategies Empirically Compared. *Financial Innovation*, 10, 117. <https://doi.org/10.1186/s40854-024-00643-1>
- PlanB. (2019). *Modeling Bitcoin's Value with Scarcity*. Medium. Retrieved August 31, 2026, from <https://medium.com/@100trillionUSD/modeling-bitcoins-value-with-scarcity-91fa0fc03e25>
- Shahbazi, Z., & Byun, Y.-C. (2022). Machine Learning-Based Analysis of Cryptocurrency Market Financial Risk Management. *IEEE Access*, 10, 37848-37856. <https://doi.org/10.1109/ACCESS.2022.3162858>
- Shelton, A. (2024). Bitcoin Return Prediction: Is It Possible via Stock-to-Flow, Metcalfe's Law, Technical Analysis, or Market Sentiment? *Journal of Risk and Financial Management*, 17(10), 443. <https://doi.org/10.3390/jrfm17100443>
- Wątorek, M., Drożdż, S., Kwapien, J., Minati, L., Oświęcimka, P., & Stanuszek, M. (2021). Multiscale Characteristics of the Emerging Global Cryptocurrency Market. *Physics Reports*, 901, 182. <https://doi.org/10.1016/j.physrep.2020.10.005>
- Zahid, M., Iqbal, F., & Koutmos, D. (2022). Forecasting Bitcoin Volatility Using Hybrid GARCH Models with Machine Learning. *Risks*, 10(12), 237. <https://doi.org/10.3390/risks10120237>

Zastosowanie modeli predykcyjnych w prognozowaniu cen bitcoinów i zarządzaniu ryzykiem

Streszczenie

Cel: Celem artykułu jest ocena statystycznej istotności modelu *Stock-to-Flow* (S2F) w prognozowaniu wartości bitcoina do 2030 roku oraz jego przydatności w zarządzaniu ryzykiem.

Metodyka: Wykorzystano metodę opartą na analizie ilościowej modelu *Stock-to-Flow* (S2F). Zgromadzono dane ceny bitcoina oraz odpowiadające im wartości wskaźnika S2F od 2009 do 2025 roku, które zostały sformatowane i oczyszczone ze zbędnych informacji. Następnie zdefiniowano model predykcyjny w postaci regresji logarytmiczno-liniowej. W kolejnym kroku dokonano ceny statystycznej stopnia dopasowania modelu do danych. Na końcu zostały wyznaczone konkretne wartości prognozowanych oraz identyfikacja potencjalnych punktów zwrotnych w cyklach cenowych.

Wyniki: Wyniki analizy ilościowej opartej na modelu *Stock-to-Flow* (S2F) wskazują na silną statystyczną relację między rzadkością bitcoina, a jego ceną rynkową w badanym okresie. Model S2F pomimo swoich ograniczeń uwzględniających wyłącznie stronę podażową, pomijając gwałtowne zmiany po

stronie popytowej, wykazuje wysoką zdolność predykcyjną dla trendów średniookresowych i umożliwia identyfikację faz rynkowych, co czyni go użytecznym instrumentem w procesie ograniczania ryzyka inwestycyjnego.

Implikacje i rekomendacje: Model *Stock-to-Flow* jest narzędziem pomocnym w ocenie długoterminowej dynamiki podaży bitcoinów oraz roli cykli halvingowych jako mechanizmu deflacyjnego. W kontekście zarządzania ryzykiem na rynkach finansowych oferuje on użyteczną ramę czasową do zidentyfikowania cyklicznych wzorców i wspomagania decyzji alokacyjnych w horyzoncie wieloletnim. Dla zwiększenia skuteczności zarządzania ryzykiem powinien stanowić element hybrydowy z innymi metrykami *on-chain* (np. liczba nowych użytkowników sieci, cena ich zakupu) czy miarami ryzyka, takimi jak VaR.

Oryginalność/wartość: Wykorzystanie kryptowalut i modeli predykcyjnych w zarządzaniu ryzykiem na rynkach finansowych pokazało wymierne korzyści, wynikające z ich zastosowania. Oszacowano potencjał średniookresowych modeli do przewidywania przyszłych wartości oraz oceny ich przydatności w skutecznej strategii zarządzania ryzykiem inwestycyjnym na dojrzewającym rynku kryptowalut.

Słowa kluczowe: model predykcyjny, model *Stock-to-Flow*, bitcoin
