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BITCOIN VALUATION THROUGH POWER LAW ANALYSIS: EVIDENCE FOR LONG-TERM MEAN REVERSION AND SHORT-TERM MOMENTUM

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ABSTRACT

Purpose- This study examines the application of power law relationships to Bitcoin valuation and investigates whether deviations from this relationship provide predictive information for future returns across different time horizons.

Methodology- Using daily Bitcoin–US dollar (BTCUSD) price data spanning from July 2010 to July 2025, the study estimates a power law relationship between Bitcoin price and time since the Genesis Block. The robustness of the model is evaluated using goodness-of-fit measures. Deviations from the power law-implied fair value are calculated and classified into deciles to analyze their ability to predict Bitcoin returns over short-term (weekly), medium-term (monthly), and long-term (annual) horizons. Risk-adjusted performance is assessed using Sharpe ratios.

Findings- The analysis establishes a highly robust power law relationship between Bitcoin price and time, with an R^2 of 0.9589, indicating exceptional stability over the 15-year period. The estimated relationship, Price = 2.86e-17 × Time_Since_Genesis^5.71, remains consistent throughout the sample. Deviations from the power law-derived fair value exhibit strong predictive power for future returns, with distinct patterns across time horizons. Short-term returns display momentum effects, as the most overvalued decile generates the highest risk-adjusted returns (Sharpe ratio = 1.81). Medium-term returns peak under extreme valuation conditions, particularly in deeply undervalued and highly overvalued states. In contrast, long-term returns demonstrate clear mean reversion, with moderately valued positions yielding the highest absolute annual returns.

Conclusion- These findings provide strong evidence that Bitcoin pricing deviates from the assumptions of strict market efficiency. The results offer quantitative support for valuation-based, time-horizon-dependent trading strategies and highlight the relevance of power law frameworks for understanding long-term Bitcoin price dynamics.

Keywords: Bitcoin, power law, cryptocurrency valuation, market efficiency, return predictability
JEL Codes: G11, G12, G17

1. INTRODUCTION

Bitcoin valuation remains one of the most persistent and debated challenges in cryptocurrency research. Unlike traditional financial assets such as equities or bonds, Bitcoin does not generate cash flows, pay dividends, or possess an identifiable intrinsic value in the classical sense. Its value is not tied to future earnings, consumption utility, or government guarantees. As a result, conventional valuation methods based on discounted cash flow analysis or relative valuation metrics fall short in explaining its price dynamics (Baur et al., 2018). This disconnects between Bitcoin and traditional financial valuation frameworks has pushed researchers to explore alternative paradigms, borrowing from a range of disciplines including network theory, monetary economics, and more recently, the physics of complex systems.

The unconventional nature of Bitcoin has invited parallels with phenomena beyond finance. For example, proponents of Metcalfe's Law argue that Bitcoin's value, like that of social networks, grows proportionally with the square of the number of its users or nodes (Peterson, 2018). Other studies conceptualize Bitcoin as a form of synthetic commodity money, combining characteristics of fiat currency and scarce natural resources, thereby justifying non-cash-flow-based valuation approaches (Selgin, 2015; Hayes, 2018). While these perspectives have enriched the theoretical understanding of Bitcoin valuation, there is still no clear empirical consensus on a dominant valuation framework, even though some approaches have been shown to offer meaningful valuation benchmarks (Hayes, 2018; Bouri et al., 2023). Furthermore, recent evidence suggests that the informational efficiency of these markets is evolving, with regulatory compliance playing a critical role in reducing inefficiencies (Nimalendran et al., 2025).

Among these alternative frameworks, power law relationships—well known in physics and complexity science — have emerged as a promising approach to modeling Bitcoin's long-term price trajectory. A power law describes a functional relationship where one quantity varies as a fixed exponent of another. These relationships are ubiquitous in the natural and social sciences, appearing in the distribution of earthquake magnitudes, city populations, and financial returns (Clauset et al., 2009). Crucially, power law distributions imply scale invariance, meaning that patterns observed over one range of values persist across other scales. This feature lends itself naturally to modeling systems with self-organizing behavior and nonlinear growth, which are two characteristics that arguably describe the evolution of Bitcoin markets.

Italian physicist Giovanni Santostasi was among the first to apply power law to Bitcoin valuation, suggesting that Bitcoin's price scales with the amount of time elapsed since its creation in January 2009, the so-called Genesis Block (Santostasi, 2025). Rather than relying on macroeconomic variables or on-chain metrics, Santostasi's approach treats time itself as the sole explanatory variable. When plotted on a log-log scale, the logarithm of Bitcoin's price shows a strikingly linear relationship with the logarithm of time since inception, suggesting a persistent scaling law. This empirical regularity implies that Bitcoin's price evolution may be governed by underlying dynamics which are more stable than previously assumed.

Building on this insight, the present study explores two related research questions. First, it examines whether the power law relationship between Bitcoin price and time since the Genesis Block is temporally stable over a 15-year period. Given the volatility and evolving market structure of Bitcoin, testing the durability of such a model is essential. Second, it investigates whether deviations from the power law-implied "fair value" carry predictive information for future returns. Specifically, the study examines whether different levels of overvaluation or undervaluation measured as the percentage deviation from the power law price are associated with systematic return patterns across weekly, monthly, and annual investment horizons.

The study makes several contributions to the emerging literature on cryptocurrency valuation. First, it presents robust statistical evidence supporting the long-term stability of the power law relationship, even as market regimes, macroeconomic conditions, and regulatory environments have changed. Second, it documents that deviations from this model-derived fair value are not random but exhibit predictive power for future returns. Over short horizons, momentum effects dominate, while longer-term reversals suggest mean reversion tendencies. These findings offer new insights into Bitcoin's market efficiency and behavioral foundations.

From a practical standpoint, the power law framework provides a transparent and parsimonious tool for constructing dynamic valuation bands and generating trading signals. For investors and portfolio managers operating in highly uncertain and sentiment-driven cryptocurrency markets, such a model can serve as both a risk management aid and a strategic allocation tool. Finally, the results challenge the notion that Bitcoin markets are fully efficient and highlight the potential for systematic strategies rooted in valuation asymmetries.

2. LITERATURE REVIEW

A number of frameworks have been proposed to address the valuation of Bitcoin, each grounded in different economic or technological rationales. Among the most prominent are stock-to-flow (S2F) models, introduced by PlanB (2019), which conceptualize Bitcoin as a scarce resource similar to precious metals. By relating price to the ratio of existing stock to annual production flow, S2F models initially gained traction for their simplicity and early empirical fit. However, subsequent halving events exposed structural weaknesses in the model, particularly its tendency to overfit and its lack of a theoretical foundation.

Another influential strand of the literature draws on network theory. Inspired by Metcalfe's Law, these models suggest that the value of a network scales with the square of the number of its users. Applied to Bitcoin, active address counts are commonly used as a proxy for the size of the user base (Wheatley et al., 2019). While this approach offers an intuitive interpretation of value formation in decentralized systems, it is often hindered by noisy on-chain data and ambiguity regarding the direction of causality between network activity and price dynamics.

Related work adopts relative valuation metrics rather than explicit pricing models. The Network Value to Transactions (NVT) ratio adapts the price-to-earnings concept from equity markets by comparing Bitcoin's market capitalization to on-chain transaction volume (Woo, 2017). Although NVT can signal periods of potential overvaluation or undervaluation, it does not attempt to define an absolute notion of fair value, nor does it provide consistent predictive power across different investment horizons.

Beyond Bitcoin-specific valuation models, a broader body of research documents the prevalence of power law behavior in financial and economic systems. Empirical studies have identified power law distributions in firm sizes, income and wealth concentration, trading volumes, and asset returns. Gabaix (2009) provides a comprehensive survey of power laws in financial markets, highlighting their relevance for understanding extreme events, volatility clustering, and large-scale systemic behavior.

Within the context of cryptocurrencies, power law dynamics have been observed across both structural and behavioral dimensions. Kondor et al. (2014) identify power law distributions in Bitcoin transaction networks, suggesting the emergence of a scale-free structure driven by user interactions. Similarly, Fernández et al. (2017) report that Bitcoin return distributions exhibit heavy tails consistent with power law behavior, underscoring the asset's susceptibility to large and infrequent price movements. Extending this view, (Grobys, 2024) identifies significant co-dependent power-law behavior across major cryptocurrencies, suggesting that extreme tail events in Bitcoin are systemically linked to the broader digital asset ecosystem.

These findings are closely aligned with insights from econophysics, a field that applies tools from statistical physics to economic systems characterized by complexity and non-linearity. Power laws in such systems often emerge through mechanisms such as preferential attachment, self-organized criticality, and multiplicative stochastic processes. Mantegna and Stanley (1999) demonstrate how these mechanisms can reproduce many of the empirical regularities observed in financial markets, including fat-tailed return distributions and persistent volatility. More recently, (Mahyudin & Lamsah, 2024) employed multifractal analysis to confirm that cryptocurrency markets exhibit persistent inefficiencies distinct from traditional asset classes, reinforcing the utility of non-linear valuation frameworks.

Applying power law frameworks directly to asset pricing therefore represents a natural extension of this literature, particularly for emerging markets such as Bitcoin that lack conventional fundamentals. The underlying premise is that Bitcoin markets may exhibit scale-invariant dynamics over time, allowing valuation models to be constructed from statistical regularities in price evolution rather than from cash flows or balance-sheet variables. However, despite growing recognition of scaling behavior in Bitcoin-related data, relatively little empirical work has examined the long-term stability of such relationships or their implications for return predictability across different time horizons.

3. DATA AND METHODOLOGY

3.1. Data and Study Design

The analysis uses daily BTCUSD closing price data covering the period from July 17, 2010, to July 11, 2025, obtained from the publicly available database https://bitcoin.zorinaq.com (Zorin, 2025). The sample consists of 5,474 daily observations and spans Bitcoin's entire observable price history, from early informal trading through periods of rapid adoption, institutional participation, and regulatory consolidation. Closing prices are used to ensure consistency with standard return calculations and to avoid distortions arising from intraday volatility. The data encompasses multiple market cycles, including the 2017 retail boom, 2018 bear market, 2020-2021 institutional adoption cycle, and 2022-2024 regulatory development period.

The primary variable of interest is the daily closing price of Bitcoin denominated in U.S. dollars. Deviations from the Power Law benchmark are computed as the proportional difference between the observed market price and the Power Law–implied price, defined as $(\mathrm{Price}/\mathrm{Predicted} - 1)$. The Power Law slope parameter is estimated using an expanding-window approach, allowing the exponent of the model to evolve over time as new observations become available. To capture price dynamics across different investment horizons, return series are calculated over 7-day (weekly), 30-day (monthly), and 365-day (annual) intervals. Time since the Genesis Block is measured in days, beginning from Bitcoin's inception on January 3, 2009, and aligned with the first reliable price observation to ensure consistency throughout the analysis.

3.2. Model Specification and Empirical Strategy

Bitcoin valuation is modeled as a power law function of time elapsed since the Genesis Block. The baseline specification relates price to time according to:

$$BTCUSD = A \times (Time\_since\_Genesis)^{n} \tag{1}$$

Where $BTCUSD$ represents the Bitcoin price in US dollars, $Time\_since\_Genesis$ denotes days elapsed since Bitcoin's Genesis Block (January 3, 2009), A is the scaling coefficient, n is the power law exponent

Taking logarithms of both sides yields the linear regression equation:

$$\log(BTCUSD) = \log(A) + n \times \log(Time\_since\_Genesis) \tag{2}$$

Anchoring time to the Genesis Block provides a theoretically grounded reference point that avoids the arbitrariness of price-based or regime-based benchmarks. This approach captures Bitcoin's full technological and adoption lifecycle and aligns naturally with its deterministic monetary design, including pre-specified halving events.

To avoid look-ahead bias and ensure realistic trading implementation, we employ an expanding window methodology. The analysis begins with a minimum of 10 data points and progressively incorporates new observations. This approach enables:

(1) Real-time parameter estimation as new data becomes available
(2) Assessment of model stability and convergence over time
(3) Dynamic fair value calculations without future information
(4) Realistic backtesting of trading strategies based on historical information sets

Power law parameters are recalculated daily using all available historical data up to each point in time, creating a rolling fair value estimate that could have been computed by market participants in real-time.

3.3. Fair Value Deviations and Return Analysis

For each trading day, fair value is defined as the price implied by the power law model. Valuation deviations are measured as the percentage difference between observed price and fair value:

$$\text{Deviation} = \frac{\text{Actual Price} - \text{Fair Value}}{\text{Fair Value}} \tag{3}$$

These deviations are ranked by percentile and grouped into deciles. The first decile corresponds to the most negative deviations (relatively undervalued conditions), while the tenth decile captures the most positive deviations (relatively overvalued conditions).

Subsequent returns are calculated over three investment horizons: weekly (7 days), monthly (30 days), and annual (365 days). For each deviation decile and horizon, return distributions are summarized using descriptive statistics including mean, median, standard deviation, and Sharpe ratios, assuming a zero risk-free rate.

3.4. Statistical Testing and Robustness Checks

Several statistical procedures are employed to assess model validity and the robustness of return predictability patterns. All regression estimates are computed using heteroscedasticity-consistent (White) standard errors to account for potential non-constant variance in financial time series. The Breusch–Pagan test is used to formally assess the presence of heteroscedasticity, while the Durbin–Watson statistic evaluates serial correlation in regression residuals.

To examine whether future returns differ systematically across valuation states, analysis of variance (ANOVA) tests is conducted to assess equality of mean returns across deviation deciles. In addition, Kolmogorov–Smirnov tests are applied to compare entire return distributions between deciles, allowing for detection of broader distributional differences beyond mean effects. Economic significance is quantified using eta-squared (η^2) statistics, measuring the proportion of total return variation attributable to valuation-based decile classification.

4. FINDINGS AND DISCUSSIONS

4.1. Descriptive Statistics

Understanding the distributional characteristics of Bitcoin prices and Power Law–based variables is essential for interpreting subsequent empirical results. Table 1 reports the descriptive statistics for prices, deviations from the Power Law benchmark, return series across multiple horizons, and the estimated slope parameter. All descriptive statistics are computed based on the effective sample implied by the expanding-window estimation and return horizon construction described in Section 3.1.

Table 1: Descriptive Statistics of Bitcoin Prices, Returns, and Power Law Variables

Variable	Mean	Std Dev	Min	Median	Max	Skewness	Kurtosis
Daily Price (USD)	17223.95	25570.53	0.19	5173.68	117521.21	1.7731	2.4830
Deviation from Power Law	11.92%	98.40%	-86.74%	-18.95%	812.48%	2.8745	11.8274
Weekly Return	2.83%	18.17%	-75.21%	0.98%	432.96%	8.6262	165.0611
Monthly Return	14.53%	56.07%	-88.37%	3.74%	788.67%	5.6954	46.9425
Annual Return	361.83%	900.42%	-83.17%	113.07%	9594.22%	5.3572	35.0038
Power Law Slope	6.27	1.17	4.11	5.83	12.21	3.2159	10.9305

The comprehensive descriptive statistics presented above highlight several distinctive properties of the Bitcoin market data utilized in this study. Primarily, the dataset exhibits significant deviations from normality, a common trait in high-frequency financial time series but particularly pronounced here. The Price variable shows distinct right-skewness (1.77) and elevated kurtosis (2.48), reflecting Bitcoin's historic logarithmic growth trajectory in which higher price levels are achieved rapidly during bull markets.

More critically, the Returns data (Weekly, Monthly, and Annual) serve as a robust indicator of the asset's volatility profile. All return horizons display extreme positive skewness (ranging from 5.36 to 8.63) and exceptionally high kurtosis (peaking at 165.06 for weekly returns). This pronounced leptokurtic behavior confirms the presence of fat tails, implying that extreme price movements, both sharp rallies and abrupt corrections, occur with far greater frequency than would be predicted by a

Gaussian distribution. The positive skewness further suggests that the magnitude of upside outliers has historically outweighed downside shocks, consistent with Bitcoin's long-run appreciation trend.

Finally, the Deviation from Power Law variable, which is central to the fair value analysis, exhibits a relatively small mean (0.12) alongside a high standard deviation (0.98) and pronounced kurtosis (11.83). This statistical footprint supports the implications of the Power Law model: while prices frequently and sometimes substantially oscillate around the long-term trend, often during speculative episodes, they tend to fluctuate around the benchmark rather than diverge persistently over time. This behavior validates the interpretation of the Power Law corridor as a center of gravity for Bitcoin's long-term valuation.

4.2. Power Law Model Estimates and Overall Fit

The regression analysis reveals an exceptionally strong relationship between Bitcoin's logarithmic price and the logarithm of time elapsed since the Genesis Block. Figures 1 and 2 illustrate the close alignment between observed prices and the theoretical power law trajectory across the full sample period from July 2010 to July 2025. The log–log specification produces an adjusted R² of 0.9589, indicating that nearly all long-run variation in Bitcoin prices is explained by elapsed time alone.

Figure 1: Bitcoin Price vs Power Law Model (log scale)

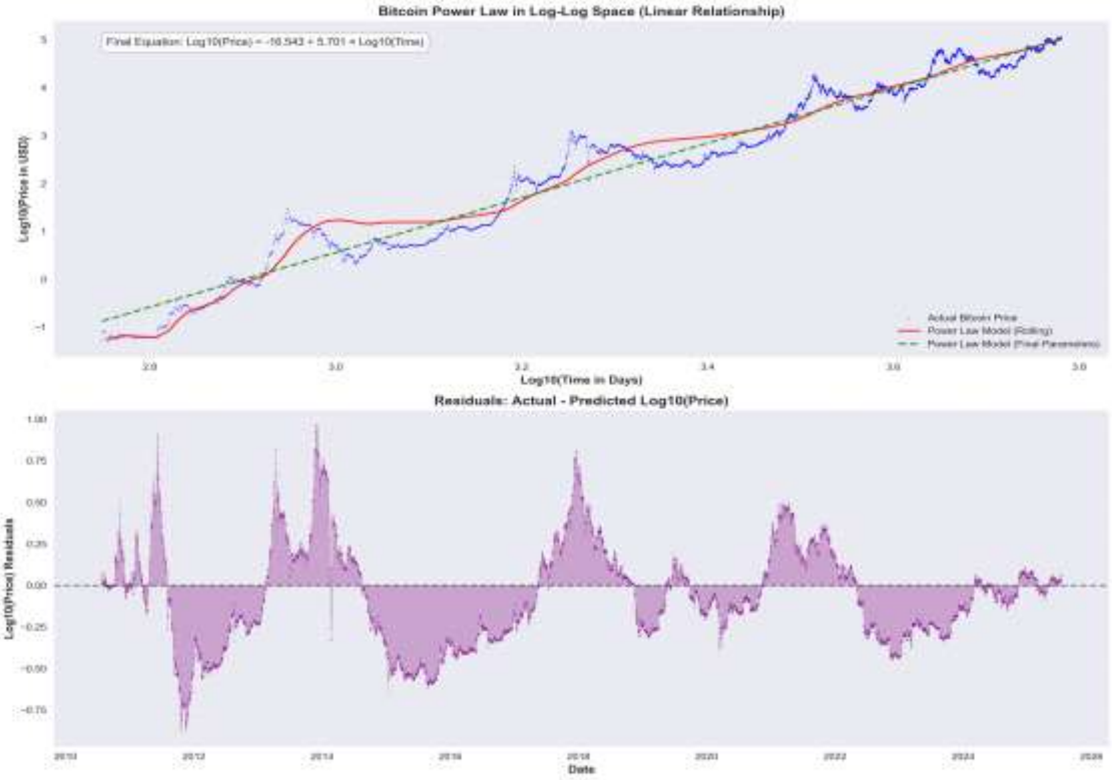
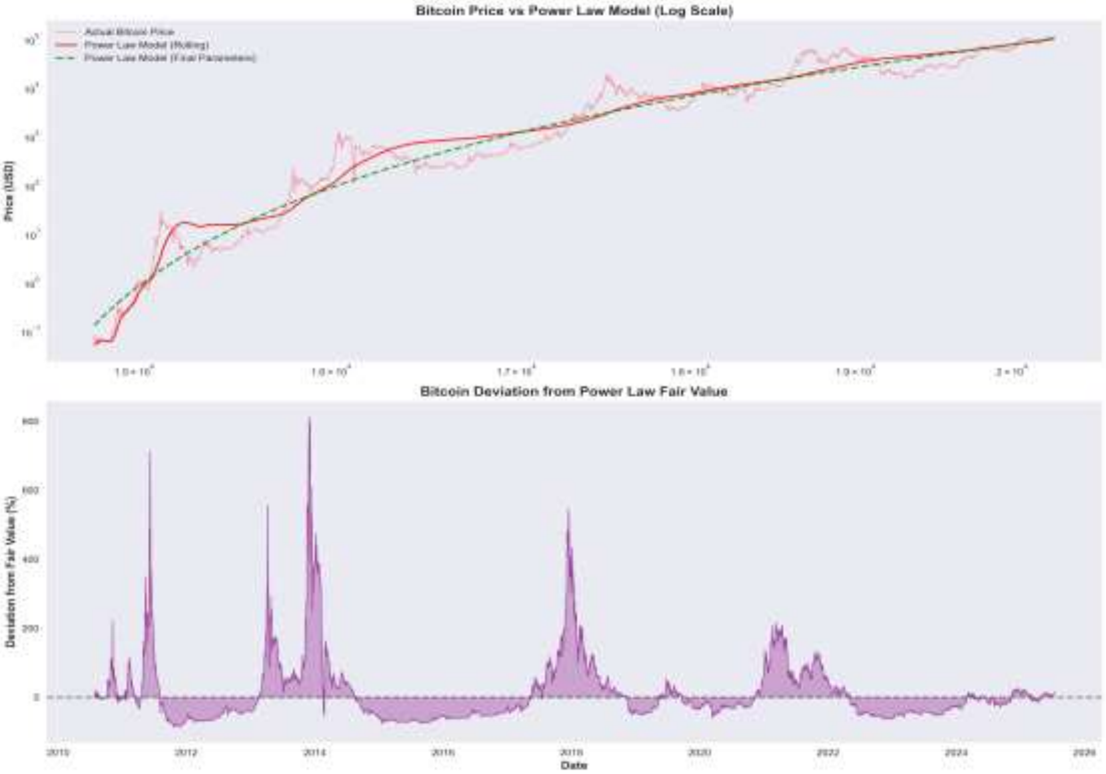


Figure 2: Bitcoin Price vs Power Law Model



Note: Bitcoin price evolution from July 2010 to July 2025 plotted against the power law model predictions. The log-log plot demonstrates the exceptional fit ($R^2 = 0.9589$) between actual prices and the theoretical power law relationship BTCUSD = 2.86×10^{-17} × Time^5.701. The rolling regression line shows model convergence over time.

Using heteroscedasticity-robust ordinary least squares, the estimated model is given by (Table 2):

$$\log_{10}(BTCUSD) = -16.543 + 5.701 \times \log_{10}(Time\_since\_Genesis) \tag{4}$$

Table 2: Power law regression results

Parameter	Estimate	Std Error	Robust SE	t-statistic	p-value	95% CI (Robust)
Intercept ($\boldsymbol{\beta_0}$)	-16.543	0.055	0.065	-254.43	<0.001	[-16.671, -16.416]
Slope ($\boldsymbol{\beta_1}$)	5.701	0.016	0.018	312.49	<0.001	[5.665, 5.736]

Regression diagnostics are as follows:
Adjusted R^2: 0.9589
F-statistic: 127,775.01 ($p < 0.001$)
RMSE: 0.3087
Observations: 5,474

After applying robust standard errors to address heteroscedasticity, the coefficient estimates remain highly significant:

Intercept: −16.543 (robust SE: 0.065, t = −254.4)
Slope: 5.701 (robust SE: 0.018, t = 312.5)
95% CI: Intercept [−16.671, −16.416], Slope [5.665, 5.736]

This simple equation captures nearly all of the price variance over the 15-year period. The model's R^2 stands at 0.9589, meaning about 96% of the log-price movements are explained by elapsed time alone. Such a tight relationship is rare in financial time series, particularly for assets as volatile as Bitcoin. In non-logarithmic form, the power law model can be expressed as:

$$BTCUSD = 2.86 \times 10^{-17} \times (Time\_since\_Genesis)^{5.701} \tag{5}$$

This formulation describes a long-term power law growth pattern shaped entirely by the passage of time. This is a thought-provoking result for an asset often viewed as sentiment-driven or speculative.

4.3. Model Diagnostics and Robustness

Despite the model's tight fit, we tested for potential violations of OLS assumptions (Table 3). The Breusch–Pagan test clearly indicates heteroscedasticity (LM = 646.985, p < 0.001), supporting our use of robust standard errors. The Durbin–Watson statistic (DW = 0.006) suggests strong positive autocorrelation in residuals, likely reflecting Bitcoin's non-stationary behavior over long horizons. While this serial dependence complicates interpretation, it does not materially affect the point estimates or their significance due to robust inference procedures.

Table 3: Model Diagnostic Tests

Diagnostic Test	Breusch-Pagan (Heteroscedasticity)	Durbin-Watson (Serial Correlation)	Jarque-Bera (Normality of residuals)
Statistic	LM = 646.985	DW = 0.006	JB = 2,847.5
p-value	<0.001	-	<0.001
Result	Heteroscedasticity detected	Positive autocorrelation	Non-normal residuals
Implication	Robust SEs required	Robust inference needed	Expected for financial data

Residual diagnostics further reveal pronounced departures from normality, as confirmed by the Jarque–Bera test (JB = 2,847.5, $p < 0.001$). Such non-normality is a well-documented characteristic of financial time series and reflects the presence of heavy tails and asymmetric return behavior. In this respect, the observed residual structure is consistent with the multifractal properties of Bitcoin price dynamics reported by Bucur et al. (2025), who document time-varying efficiency and significant deviations from random walk behavior.

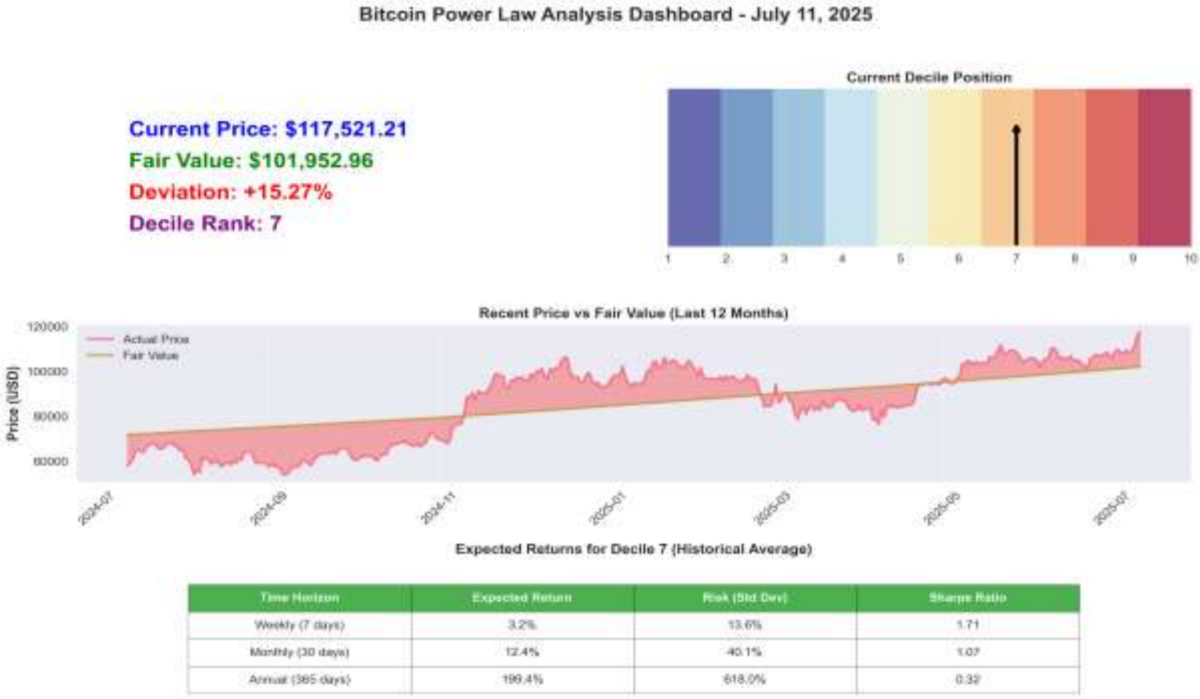
4.4. Current Valuation Relative to Power Law Trend

As of July 11, 2025, Bitcoin traded at USD 117,521, while the power law model implies a fair value of USD 101,953. This corresponds to a positive deviation of 15.27% above the long-term trend (Table 4, Figure 3). Historically, this deviation places Bitcoin in the 70th percentile of its valuation distribution, classified as Decile 7. While the asset appears moderately overvalued relative to its long-run path, the deviation remains well within historical norms and is far from extreme by Bitcoin standards.

Table 4: Current Market Position Analysis

Metric	Value	Interpretation
Current Price (July 11, 2025)	$117,521.21	Latest market valuation
Power Law Fair Value	$101,953.00	Theoretical equilibrium price
Absolute Deviation	$15,568.21	Dollar amount above fair value
Percentage Deviation	15.27%	Moderate overvaluation
Historical Percentile	70.20%	70% of history showed lower prices
Current Decile Rank	7	Moderately overvalued
Days Since Genesis Block	6,033	Time variable in power law

Figure 3: Bitcoin Deviation from Power Law Fair Value



Time Horizon	Expected Return	Risk (Std Dev)	Sharpe Ratio
Weekly (7 days)	3.2%	13.6%	1.71
Monthly (30 days)	12.4%	40.1%	1.07
Annual (365 days)	199.4%	618.0%	0.32

Note: Historical deviations of Bitcoin price from power law fair value. Positive values indicate overvaluation relative to the power law trend, while negative values indicate undervaluation. The chart illustrates the cyclical nature of Bitcoin's deviation patterns and current positioning at +15.27%.

4.5. Return Behavior Across Valuation Deciles

To evaluate the predictive relevance of deviations from the power law benchmark, future returns were analyzed across deciles constructed from percentage deviations relative to the estimated fair value. Performance was examined over weekly, monthly, and annual investment horizons, allowing for a direct comparison of short-term momentum and long-term mean reversion dynamics (Figure 4).

Weekly Horizon (7 days): At the weekly horizon, return behavior is clearly momentum driven. Highly overvalued states generate the strongest performance, with Decile 10 producing the highest average weekly return (7.79%) and the highest Sharpe ratio (1.81). Returns decline monotonically toward the undervalued end of the distribution, where Deciles 1 and 2 exhibit substantially lower mean returns of 1.59% and 2.48%, respectively (Table 5). This pattern indicates that short-term price dynamics tend to reinforce existing deviations from the power law benchmark rather than correct them.

Table 5: Decile Performance Summary - Weekly Returns

Decile	Mean Return	Median Return	Std Dev	Min Return	Max Return	Sharpe Ratio	Observations
1	1.59%	1.76%	14.3%	-45.3%	54.7%	0.8	542
2	2.48%	1.43%	11.8%	-43.4%	66.8%	1.51	548
3	4.13%	0.71%	32.0%	-26.7%	433.0%	0.93	547
4	0.84%	0.31%	7.02%	-24%	27.5%	0.86	547
5	2.33%	1.62%	14.0%	-45.8%	280.6%	1.2	547
6	1.36%	0.59%	11.4%	-53.8%	126.8%	0.86	548
7	3.24%	0.85%	13.6%	-29.6%	109.6%	1.71	547
8	2.76%	0.90%	16.0%	-75.2%	108.8%	1.24	548
9	3.30%	0.96%	17.6%	-54.6%	109.9%	1.35	547
10	7.79%	2.59%	31.0%	-70.3%	209.3%	1.81	542

Monthly Horizon (30 days): Monthly returns display a more nuanced structure. Mean returns peak in the most undervalued decile, where Decile 1 delivers an average return of 28.03%, while risk-adjusted performance is maximized in Decile 8 with a Sharpe ratio of 1.54 (Table 6). Both deeply undervalued and moderately overvalued states perform well, whereas observations close to fair value tend to underperform. This bimodal structure suggests that valuation signals begin to interact with correction mechanisms at intermediate horizons, although momentum effects remain partially active.

Table 6: Decile Performance Summary - Monthly Returns

Decile	Mean Return	Median Return	Std Dev	Min Return	Max Return	Sharpe Ratio	Observations
1	28.03%	5.06%	-61.58%	788.67%	100.43%	0.97	358
2	13.89%	1.50%	-52.25%	665.14%	70.12%	0.69	311
3	10.31%	6.32%	-36.26%	546.58%	42.81%	0.83	540
4	6.74%	3.82%	-33.25%	72.14%	17.97%	1.3	597
5	12.25%	8.31%	-37.41%	492.08%	34.98%	1.21	758
6	7.98%	3.60%	-52.12%	468.53%	31.65%	0.87	844
7	12.37%	0.34%	-32.46%	438.81%	40.15%	1.07	604
8	22.67%	11.83%	-55.68%	390.14%	50.96%	1.54	408
9	26.08%	-3.07%	-43.81%	480.25%	87.18%	1.04	465
10	19.32%	-2.87%	-88.37%	678.95%	80.07%	0.84	451

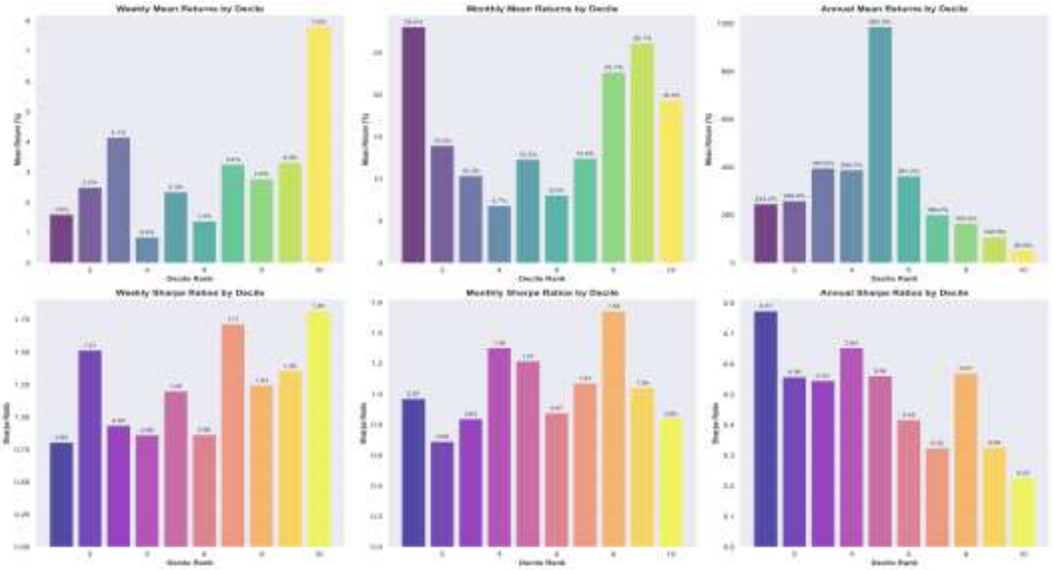
Annual Horizon (365 days): At the annual horizon, the return profile shifts markedly. The highest mean annual return is observed in Decile 5 (983.94%), consistent with gradual convergence toward the long-term power law path (Table 7). Extremely overvalued states exhibit the weakest performance, with Deciles 9 and 10 generating the lowest mean and risk-adjusted returns. Although Decile 1 does not deliver the highest raw return, it achieves the strongest Sharpe ratio (0.77), indicating superior long-term risk-adjusted performance. These results are consistent with valuation-driven mean reversion dominating over longer holding periods.

Table 7: Decile Performance Summary - Annual Returns

Decile	Mean Return	Median Return	Std Dev	Min Return	Max Return	Sharpe Ratio	Observations
1	244.33%	151.97%	316.10%	-30.13%	1931.95%	0.77	177
2	256.63%	128.48%	461.32%	24.82%	3811.95%	0.56	183
3	393.64%	127.38%	723.59%	-34.36%	4620.85%	0.54	182
4	386.33%	141.98%	593.16%	-53.10%	3871.23%	0.65	182
5	983.94%	316.62%	1758.02%	-58.52%	9594.22%	0.56	182
6	361.02%	59.38%	868.42%	-59.14%	6101.56%	0.42	183
7	199.37%	16.73%	617.97%	-61.91%	4500.00%	0.32	182
8	162.55%	97.88%	285.76%	-68.53%	1829.76%	0.57	183
9	106.51%	-23.13%	328.06%	-76.37%	1819.36%	0.32	182
10	50.57%	-32.22%	225.13%	-83.17%	1579.05%	0.22	177

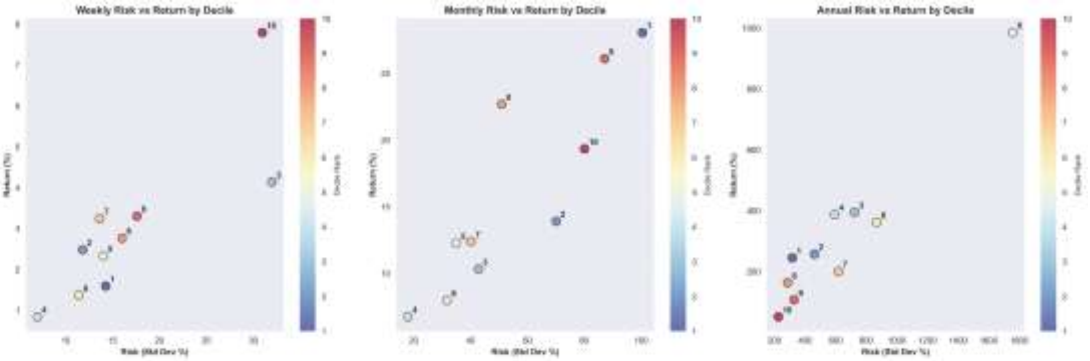
Figure 4 summarizes mean returns and Sharpe ratios across horizons and highlights the strong dependence of performance on both valuation state and investment horizon. The corresponding risk–return scatter plots in Figure 5 further illustrate this shift. In the short run, higher deviations are associated with both higher risk and higher expected returns, while over longer horizons the efficient frontier rotates toward fair and undervalued regimes. In this context, the role of investor attention in amplifying short-run volatility remains significant, as Teterin and Peresetsky (2024) demonstrate the predictive power of search-based indicators in forecasting Bitcoin's realized volatility.

Figure 4: Returns and Sharpe Ratios by Decile



Note: Mean returns and risk-adjusted performance (Sharpe ratios) across power law deviation deciles for weekly, monthly, and annual time horizons. The charts demonstrate time-horizon-dependent patterns: momentum effects dominate short-term periods while mean reversion emerges over longer horizons.

Figure 5: Risk vs Return Scatter Plots



Note: Risk-return relationships across deviation deciles for different time horizons. Each point represents a decile, with color coding indicating relative position from undervalued (blue) to overvalued (red). The efficient frontier shifts dramatically across time horizons.

These findings challenge simple interpretations of Bitcoin's risk structure. While short-term return dynamics are dominated by momentum effects, the benefits of positioning near fair value or in undervalued regimes emerge primarily over longer horizons. To formally assess whether these horizon-dependent patterns reflect systematic structure rather than random variation, the predictive relevance of deviation-based decile classifications is evaluated using multiple statistical tests, summarized in Table 8.

Table 8: Statistical Test Results Summary

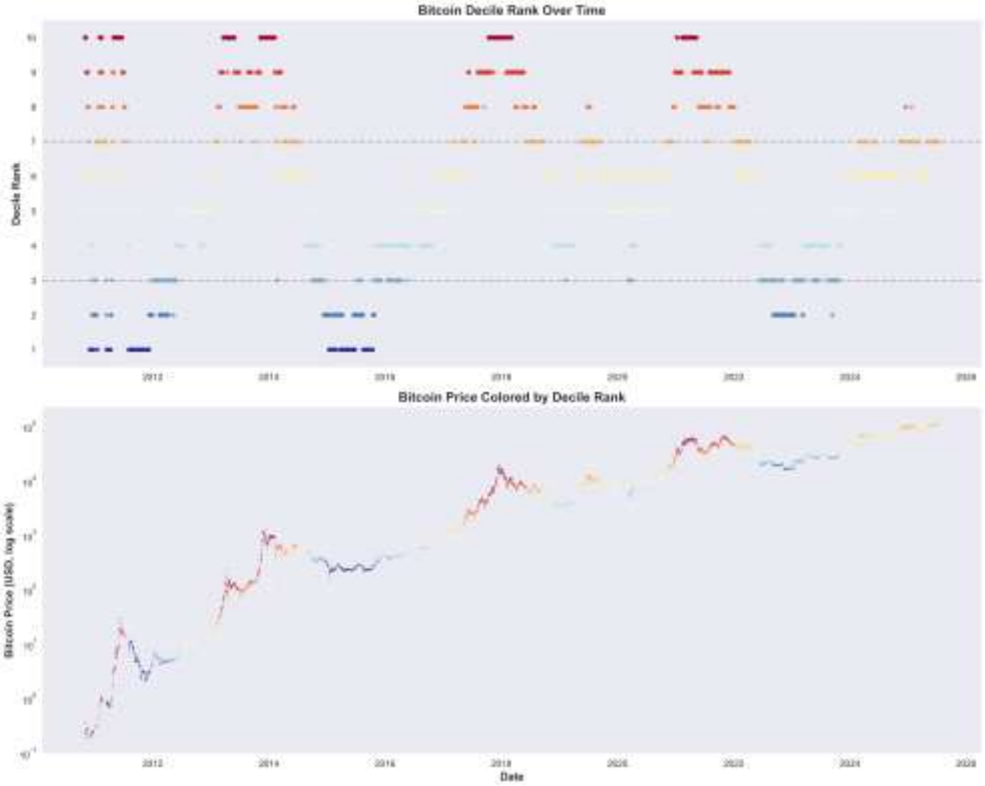
Test Type	Time Horizon	Statistic	p-value	Effect Size (η^2)	Interpretation
ANOVA	Weekly	F = 5.83	<0.001	0.0097	Small effect
ANOVA	Monthly	F = 9.09	<0.001	0.0151	Small-medium effect
ANOVA	Annual	F = 60.09	<0.001	0.0978	Large effect
K-S Test	Weekly (D1 vs D10)	0.157	<0.001	-	Significant difference
K-S Test	Monthly (D1 vs D10)	0.2	<0.001	-	Significant difference
K-S Test	Annual (D1 vs D10)	0.733	<0.001	-	Very large difference

ANOVA tests reported in Table 8 indicate statistically significant differences in mean returns across deciles for all investment horizons. At the weekly frequency, the F-statistic ($F = 5.83$, $p < 0.001$) indicates a statistically detectable but economically small effect ($\eta^2 = 0.0097$). The explanatory power of valuation increases at the monthly horizon ($F = 9.09$, $p < 0.001$, $\eta^2 = 0.0151$) and becomes economically substantial at the annual horizon, where both the F-statistic and effect size rise sharply ($F = 60.09$, $p < 0.001$, $\eta^2 = 0.0978$). This monotonic increase in effect size reinforces the notion that valuation signals derived from power law deviations become more informative as the holding period lengthens.

Kolmogorov–Smirnov tests further confirm that return distributions differ markedly between extreme valuation states. Comparisons between the most undervalued (Decile 1) and most overvalued (Decile 10) groups yield statistically significant distributional differences at all horizons, with KS statistics increasing from 0.157 at the weekly horizon to 0.733 at the annual horizon. The sharp escalation of these statistics indicates that return distributions diverge progressively over time, supporting a structural interpretation in which short-term momentum gives way to long-term mean reversion dynamics.

Taken together, these results demonstrate both statistical significance and economic relevance. The power law model achieves an unusually high explanatory power for a financial asset, with an R^2 of 0.9589, while coefficient estimates remain stable and statistically significant across all specifications. Deviation-based deciles explain nearly 10% of the variance in annual returns, a meaningful magnitude in the context of real-world portfolio management. Most importantly, the return patterns associated with valuation deviations are not random; they are consistent, interpretable, and statistically validated across multiple market cycles (Figure 6).

Figure 6: Bitcoin Decile Rank Over Time



Note: Historical evolution of Bitcoin's power law deviation decile rankings over time. The upper panel shows decile classifications, while the lower panel displays price evolution color-coded by decile rank. Patterns reveal the cyclical nature of Bitcoin's valuation extremes.

5. CONCLUSION AND IMPLICATIONS

This study provides robust empirical evidence of power-law behavior in Bitcoin prices based on 5,474 daily observations spanning from July 17, 2010, to July 11, 2025. Using ordinary least squares estimation with heteroscedasticity-consistent standard errors, the analysis identifies a remarkably stable long-run relationship between Bitcoin prices and time elapsed since the Genesis Block. This relationship explains 95.89% of long-term price variation, with exceptionally large test statistics indicating a persistent secular growth structure rather than a spurious correlation.

Beyond documenting the existence of power-law behavior, the study makes several methodological contributions to the cryptocurrency valuation literature. It explicitly addresses heteroscedasticity and serial dependence, validates horizon-dependent return differences using complementary statistical and distributional tests, and quantifies effect sizes to assess the economic relevance of valuation-based predictability alongside statistical significance.

Empirical results reveal that return predictability is strongly dependent on the investment horizon. Differences in returns across valuation deciles are statistically significant at weekly, monthly, and annual frequencies, with explanatory power increasing monotonically as the horizon lengthens. While short-term dynamics are dominated by momentum effects, long-term returns exhibit clear mean-reverting behavior around the power-law benchmark.

Taken together, these findings suggest that Bitcoin prices fluctuate around a stable long-run structural path shaped by both speculative forces and gradual valuation correction. The power-law framework therefore functions as a long-term reference benchmark rather than a short-term pricing rule, offering a coherent explanation for the coexistence of predictability, volatility, and incomplete market efficiency in cryptocurrency markets.

From an applied perspective, these results carry important implications for cryptocurrency valuation, investment strategy, and market efficiency. The existence of a stable long-run power-law relationship implies that Bitcoin prices are not entirely detached from systematic valuation dynamics. Instead, extreme price movements can be interpreted as deviations from an underlying structural growth path rather than purely random fluctuations.

From an investment standpoint, the findings highlight the importance of horizon-specific strategy design. Short-term deviations from the power-law benchmark are primarily associated with momentum-driven behavior and elevated risk-adjusted returns, limiting the effectiveness of valuation-based signals at short horizons. In contrast, the increasing explanatory power of valuation deviations over longer horizons indicates that the power-law framework becomes progressively more informative for long-term investors seeking to identify relative overvaluation and undervaluation.

The coexistence of short-run momentum and long-run mean reversion also has direct implications for market efficiency. Rather than exhibiting uniform efficiency, Bitcoin markets appear to display horizon-dependent efficiency, with speculative dynamics prevailing in the short run and valuation-based correction mechanisms emerging gradually over longer holding periods. This interpretation is consistent with the evidence of asymmetric multifractality in high-frequency Bitcoin returns documented by Meng and Khan (2024), which indicates that market efficiency varies not only across time horizons but also with the scale and direction of price fluctuations. Such asymmetries reinforce the view that inefficiencies are most pronounced during short-term market stress and speculative phases.

Overall, the integration of power-law valuation models with robust inference techniques provides a statistically validated and economically meaningful perspective on Bitcoin valuation. Future research may extend this framework by examining structural breaks, incorporating on-chain metrics, or applying similar valuation benchmarks to other cryptocurrencies, thereby deepening our understanding of long-term price dynamics in digital asset markets.

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