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THE CRYPTO-EQUITY NEXUS: A ROLLING LINEAR REGRESSION ANALYSIS OF BITCOIN'S PREDICTIVE POWER ON MICROSTRATEGY AND BLACKROCK

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Abstract
This study analyzes the differing dynamics within the crypto-equity nexus by examining the influence of Bitcoin (BTC) on the valuation of MicroStrategy (MSTR), an active leveraged balance sheet adopter, and BlackRock (BLK), a passive institutional conduit. The objective is to assess the predictive effectiveness of BTC across these various corporate archetypes. We utilized Rolling Linear Regression (RLR) with both growing-window and fixed-window methodologies to evaluate the time-varying correlation and forecast accuracy for MSTR and BLK from 2020 to late 2025. This comparative analysis identified parameter instability due to changes in corporate strategy. The findings indicate that the RLR model for MSTR demonstrated considerable forecast bias, as reflected by a notably high Mean Absolute Percentage Error (MAPE), especially with the growing window. This failure indicates that MSTR functions as a non-linear, high-beta instrument, enhanced by a speculative leverage premium. The BLK model exhibited high accuracy and stability, evidenced by a low MAPE, which confirms a systematic second-order correlation based on institutional fee revenue. In conclusion, the findings indicate that BTC serves as a significant determinant for both equities, necessitating a tailored predictive modeling approach. Simple linear models are adequate for stable conduits such as BLK; however, they fail to accurately represent MSTR, where price movements are influenced by non-linear corporate financing and active leverage dynamics.

Keywords: Crypto-Equity Nexus, Rolling Regression, MicroStrategy, BlackRock, Bitcoin

1. Introduction

The integration of digital assets into the global financial framework has transitioned from a speculative niche to an essential element of institutional portfolio management. By late 2025, the "crypto-equity nexus" has emerged as a measurable economic phenomenon, with the valuations of certain publicly traded firms becoming increasingly responsive to Bitcoin (BTC) price fluctuations (Hacibedel & Ouazad, 2023; Komarudin & Magfiroh, 2024). This association is evident in two distinct corporate archetypes: the "active" balance sheet adopter, exemplified by MicroStrategy (MSTR), and the "passive" institutional conduit, represented by BlackRock (BLK) via its iShares Bitcoin Trust (IBIT).

MicroStrategy has fundamentally restructured its treasury to become a leveraged Bitcoin holding entity, effectively acting as a high-beta proxy for BTC (MicroStrategy Inc., 2024; Sigel, 2025). Conversely, BlackRock's valuation is linked to the "financialization" of cryptocurrency assets, where BTC price strength drives inflows into IBIT, augmenting fee revenue and growth sentiment (Ma, 2024). Predicting the price fluctuations of these equities, therefore, necessitates a sophisticated comprehension of

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their distinct correlations with the underlying asset. Although both are influenced by BTC volatility, the transmission mechanisms—direct and leverage-amplified for MSTR versus indirect and fee-revenue reliant for BLK—present unique forecasting difficulties. This evolving dynamic underscores the urgency of developing robust models to understand and forecast price transmission in this new asset class.

The scholarly discourse on forecasting the relationship between Bitcoin and correlated equities is divided between complex machine learning models and traditional statistical procedures. Recent comparative analyses highlight the persistent efficacy and interpretability of linear regression for examining direct correlation and causality, especially in high-volatility environments (Chen et al., 2020; Hiskiawan et al., 2025). Furthermore, several recent studies have successfully utilized Ordinary Least Squares (OLS) linear regression to analyse and forecast stock prices in relation to volatile events or variables (Bhandarkar et al., 2025; Kumari & Yadav, 2025; Manik, 2025).

However, a significant methodological gap remains. Prior studies predominantly utilize a "static" historical dataset window for regression analysis. This study bridges this gap by employing a dynamic window approach—specifically, both growing-rolling-window and fixed-rolling-window implementations of linear regression—to analyse and forecast MSTR and BLK stock prices based on BTC prices. Consequently, the formal research problem addressed is: "While existing studies predict stock prices using linear regression, our research bridges the gap by using BTC prices as a predictor variable to forecast MSTR and BLK prices, employing both growing-rolling-window and fixed-rolling-window implementations of linear regression."

The primary objective of this study is to analyse the correlation between BTC prices and MSTR/BLK stock prices and to forecast these stock prices based on BTC prices using dynamic rolling-window linear regression models. The contribution of this study is twofold: Practical/Applied Contribution: By leveraging the strong correlation between cryptocurrencies and the stocks of companies with significant crypto exposure, this study aims to provide results that serve as indicators of stock price predictability. This can equip prospective investors with advanced forecasting techniques and inform strategic decision-making. Methodological Contribution: This research contributes to the area of financial forecasting by demonstrating and validating the application of dynamic rolling-window linear regression algorithms. It provides future researchers with refined techniques for modelling price transmission in evolving and volatile market nexuses.

2. Theoretical Background

2.1 From Classical Linearity to the Crisis of Parameter Instability

The foundation of much econometric analysis is the Classical Linear Model (CLM), where the relationship between a dependent variable y and predictors X is expressed as:

$$y = X\beta + \varepsilon \tag{1}$$

The Ordinary Least Squares (OLS) estimator, under the Gauss-Markov assumptions, provides the Best Linear Unbiased Estimator (BLUE) for a constant parameter vector β (Greene, 2018; Wooldridge, 2010). This framework crucially assumes β is invariant over time—an "article of faith about the constancy of the world" (Hansen, 2001).

However, empirical reality in economics and finance is characterized by dynamic change due to shifting policy regimes, technological ruptures, and evolving agent behavior. Treating β as constant in the face of such structural changes generates "meaningless averages" and leads to significant forecast failures (Rossi, 2021; Stock &

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Watson, 2007). This empirical crisis spurred a vast literature on testing for structural breaks, from early tests like Chow (1960) and Quandt (1960) to more formal asymptotic theories (Andrews, 1993; Andrews & Ploberger, 1994) and related sequential tests (Brown et al., 1975). The pervasive evidence of parameter instability necessitates modelling frameworks that can accommodate evolving relationships.

2.2 Rolling Linear Regression as an Adaptive Solution

Rolling Linear Regression (RLR) emerges as an intuitive, non-parametric solution to model parameter evolution. It posits that while the true relationship β drifts over time, it can be treated as locally stable within a sufficiently short, moving window of k observations. Instead of a single global estimate, RLR produces a time series of local parameter estimates, {β̂_t(k)}, offering a "rolling history" of the relationship (Brand, 2006; Zivot & Wang, 2006). Formally, for a window of size k at time t, the model is:

$$y_{(t-k+1:t)} = X_{(t-k+1:t)}\, \beta_t + \varepsilon_{(t-k+1:t)} \qquad (2)$$

The local OLS estimator is calculated as:

$$\hat{\beta}_t(k) = (X'(t,k)\, X(t,k))^{-1}\, X'(t,k)\, y(t,k) \qquad (3)$$

This estimation is repeated as the window rolls forward, discarding the oldest observation and incorporating the newest. Efficient recursive computational methods, such as applying the Sherman-Morrison formula for rank-one updates, make this process manageable (Plackett, 1950).

2.3 Applications, Strengths, and Limitations of RLR

RLR's conceptual appeal and simplicity have made it a ubiquitous tool in exploratory data analysis across fields. In Finance: It is the standard method for estimating time-varying factor loadings (e.g., CAPM betas) and investigating the stability of return predictors (Cochrane, 2008; Frazzini & Pedersen, 2014). In Macroeconomics: It is used to monitor evolving policy rules, such as the Taylor Rule, and to document shifts in macroeconomic relationships like the Phillips Curve (Clarida et al., 2000; Stock & Watson, 2007).

Despite its widespread use, RLR has well-documented limitations, primarily revolving around the choice of window size (k). This choice presents a critical bias-variance trade-off: a small k yields adaptive but noisy estimates (high variance), while a large k produces smooth but sluggish estimates that smear structural breaks (high bias) (Pesaran & Timmermann, 2002; Inoue et al., 2017). Furthermore, its "boxcar" kernel gives equal weight to all observations within the window and zero weight to those outside, which can induce artificial jumps in estimates and results in the loss of initial k-1 observations.

2.4 Positioning RLR within Advanced Time-Varying Parameter Models

RLR is best viewed as a non-parametric benchmark within a broader family of Time-Varying Parameter (TVP) models. Its limitations have motivated the development of more sophisticated parametric alternatives, such as:

1) State-Space Models / Kalman Filter: Where β_t is modeled as a stochastic process (e.g., a random walk) and estimated optimally via the Kalman filter (Harvey, 2014; Durbin & Koopman, 2012). This forms the basis for models like TVP-VAR (Primiceri, 2005).
2) Markov-Switching Models: Where parameters are assumed to switch discretely between a finite number of regimes (Hamilton, 1989; Ang & Bekaert, 2002).

These models are statistically powerful but often require complex estimation, specific distributional assumptions, and can behave as "black boxes." The enduring utility of RLR lies in its transparency, simplicity, and robustness. It serves as an indispensable diagnostic tool and an honest benchmark, providing clear and interpretable insights into parameter dynamics without relying on intricate prior specifications (Engle & Manganelli, 2004; Ghosh et al., 2025).

2.5 Synthesis and Application to the Present Study

The theoretical discourse validates the use of linear regression for analysing direct asset price transmission, especially in volatile environments where interpretability is key (Chen et al., 2020; Hiskiawan et al., 2025). Given the nascent and evolving nature of the "crypto-equity nexus"—where the relationship between Bitcoin and correlated stocks like MSTR and BLK is subject to rapid shifts in market sentiment, regulatory news, and adoption phases—parameter instability is a paramount concern.

Therefore, this study adopts the RLR framework as its core methodological pillar. It simplifies the general model (Eq. 2) to a bivariate form for clarity in forecasting: $y = \beta\_0 + \beta\_1 x + \varepsilon$ *(4)*, where y represents stock price (MSTR or BLK) and x represents Bitcoin price (BTC). Crucially, we advance beyond static regression by implementing both growing-rolling-window and fixed-rolling-window variants of RLR. This dynamic approach allows the model to adapt to the evolving "beta" between these assets, directly addressing the research gap of static historical windows and providing a more nuanced tool for forecasting in this volatile inter-asset relationship.

3. Methods

3.1 Research Design and Workflow

The methodology of our research follows the systematic workflow as shown in Figure 1 below.

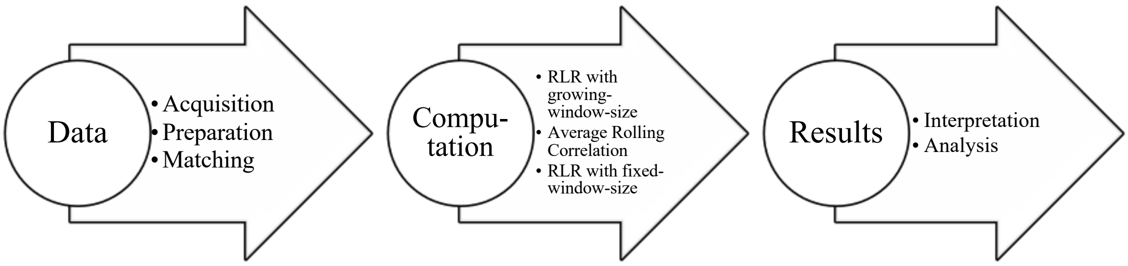

Figure 1. Research methodology workflow

First at all, as shown in Figure 1 (left), our dataset was acquired by downloading the stock price from Stooq, a Polish-based website that offers a vast amount of free downloadable historical market data (Stooq, 2000-2025). The market dataset acquired consisted of BTC, MSTR, and BLK daily market closing prices in USD, ranging from Jan 2nd, 2020 until Sep 15th, 2025. The acquired dataset then is prepared by cleaning it to the proper comma-separated-values (CSV) format. In order to be able to compute the quantities such as correlations and performing rolling linear regression, the dataset was synchronized pair-wise, namely BTC-MSTR and BTC-BLK. The synchronization is done by matching their respective corresponding dates.

The second step, as shown in Figure 1 (middle), was the computation stage. It consists of three stages:

(1) Computation of the 1-step rolling linear regression with growing-window size.

(2) Computation of average rolling correlation versus fixed-window size, where this stage is to determine the optimum correlation coefficient to be used in the stage 3.
(3) Computation of the 1-step rolling linear regression with fixed-window size.

3.2 Analysis Technique

The last step is interpretation and analysis of the forecasting results, also comparing the growing window-size and the fixed-window size results, as shown in Figure 1 (right).

The 1-step rolling linear regression with growing-window size can be briefly described as the following. The independent (or predictor) variable x is the BTC price, while the dependent variable y is the MSTR or BLK price. The implementation of linear regression model used, based on equation (3), is simply written as:

$$\hat{y} = \beta_0 + \beta_1 x \tag{4}$$

The forecast of $\hat{y}_j$, $j = (k_0 + 1), \dots, N$, is computed based on linear regression model $y_m = (\beta_0)_m + (\beta_1)_m x_m$, $m = k_0 , \dots, j$, with growing-window-size starting from k_0 to $(N - 1)$. The computation of 1-step rolling linear regression with growing-window-size is presented on Algorithm 1.

The same model, equation (4), is also used for 1-step rolling linear regression with fixed-window-size computation. The only difference is that the window size is kept fixed. The computation of 1-step rolling linear regression with fixed-window-size is presented on Algorithm 2.

For every computation, we use Pearson correlation coefficient, r, which can be computed using equation (5),

$$r = \frac{N(\sum_{i=1}^{N} x_i y_i) - (\sum_{i=1}^{N} x_i)(\sum_{i=1}^{N} y_i)}{\sqrt{N(\sum_{i=1}^{N} x_i^2) - (\sum_{i=1}^{N} x_i)^2}\sqrt{N(\sum_{i=1}^{N} y_i^2) - (\sum_{i=1}^{N} y_i)^2}} \tag{5}$$

for N pairs of datapoint $(x_1, y_1), (x_2, y_2), \cdots, (x_N, y_N)$.

3.3 Algorithmic Implementation

The detailed logic of the algorithms can be described in the following. The univariate rolling linear regression (RLR) model we use is based on the aforementioned equations (3) and (4), which is rolled based on dataset window, with assumption of local linear relationship. The model can be written as

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i , \quad i \in [B, E], \tag{6}$$

where B and E are the beginning and end indices, i, of the window, respectively. We use ordinary least square (OLS) to estimate the parameters β_0 and β_1 by minimizing the sum of squared errors (SSE),

$$\mathrm{SSE} = \sum_{i=B}^{E} \varepsilon_i^2 = \sum_{i=B}^{E} \big(y_i - (\beta_0 + \beta_1 x_i)\big)^2. \tag{7}$$

The solutions of the OLS for each specific window for the slope β_1 and the intercept β_0 can be derived analytically as

$$\beta_1 = \frac{n(\sum_{i=B}^{E} x_i y_i) - (\sum_{i=B}^{E} x_i)(\sum_{i=B}^{E} y_i)}{n(\sum_{i=B}^{E} x_i^2) - (\sum_{i=B}^{E} x_i)^2} , \tag{8}$$

and

$$\beta_0 = \frac{(\sum_{i=B}^{E} y_i) - \beta_1(\sum_{i=B}^{E} x_i)}{n} = \bar{y} - \beta_1 \bar{x} , \tag{9}$$

respectively.

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```
// Forecast of ŷ_j , j = (k_0 + 1), … , N , based on linear regression model
// y_m = (β_0)_m + (β_1)_m x_m , m = k_0 , … , j.
Input dataset: (x_1, y_1), (x_2, y_2), ⋯ , (x_N, y_N)
For k ← k0 to (N – 1) do
    // growing window-size n = E – B + 1, B is begin, E is end
    B ← 1 ; E ← k ; n ← E – B + 1 ;
```

$$(\beta_1)_k \leftarrow \frac{n(\sum_{i=B}^{E} x_i y_i) - (\sum_{i=B}^{E} x_i)(\sum_{i=B}^{E} y_i)}{n(\sum_{i=B}^{E} x_i^2) - (\sum_{i=B}^{E} x_i)^2}$$

$$(\beta_0)_k \leftarrow \frac{(\sum_{i=B}^{E} y_i) - (\beta_1)_k(\sum_{i=B}^{E} x_i)}{n}$$

$$\hat{y}_{k+1} \leftarrow (\beta_0)_k + (\beta_1)_k x_k$$

```
End For
Output: ŷ_j, j = (k_0 + 1), … , N
```

Algorithm 1. The 1-step rolling linear regression with growing-window-size.

```
// Forecast of ŷ_j , j = (k_0 + 1), … , N , based on linear regression model
// y_m = (β_0)_m + (β_1)_m x_m , m = k_0 , … , j.
Input dataset: (x_1, y_1), (x_2, y_2), ⋯ , (x_N, y_N)
For k ← k0 to (N – 1) do
    // fixed window-size n = k0 , B is begin, E is end
    B ← k – k0 + 1 ; E ← k ; n ← k0 ;
```

$$(\beta_1)_k \leftarrow \frac{n(\sum_{i=B}^{E} x_i y_i) - (\sum_{i=B}^{E} x_i)(\sum_{i=B}^{E} y_i)}{n(\sum_{i=B}^{E} x_i^2) - (\sum_{i=B}^{E} x_i)^2}$$

$$(\beta_0)_k \leftarrow \frac{(\sum_{i=B}^{E} y_i) - (\beta_1)_k(\sum_{i=B}^{E} x_i)}{n}$$

$$\hat{y}_{k+1} \leftarrow (\beta_0)_k + (\beta_1)_k x_k$$

```
End For
Output: ŷ_j, j = (k_0 + 1), … , N
```

Algorithm 2. The 1-step rolling linear regression with fixed-window-size.

The windowing methodology as described above has three district stages of computation:

Stage 1: One-step forward growing-window size RLR: The window begins at an initial size k0 and increases by a single observation at each step. Here, for each $j \in [k_0 + 1, N]$, our model is trained on data points from 1 to (j – 1) to predict $\hat{y}_j$. This stage tests the model's performance when trained using the entire available historical dataset.

Stage 2: Selection of optimum window using local correlation: In the rolling windows, the "bias-variance trade-off" is addressed by computing the average rolling correlation $\langle r \rangle$, of r in equation (5), over varying fixed-window sizes k. Here we define the optimum window size k0, where the $\langle r \rangle$ is maximum across all k to make sure that this fixed-window size captures the strongest local predictive power.

Stage 3: One-step forward fixed-window RLR: Using the optimized k0 from stage 2, the model "rolls" forward, while keeping the window size fixed. As a new observation is added at time t, the previously oldest observation dataset before (t – k0) is neglected.

We use the Mean Absolute Percentage Error (MAPE) as a metric to quantify the accuracies of both algorithms. The MAPE is chosen, instead of standard Mean Standard

Error (MSE), because MAPE captures scale-independent forecast bias, where it is necessary as BTC and its proxies have high volatility. The MAPE can be computed as

$$\text{MAPE} = \frac{1}{m}\sum_{j=1}^{m}\left|\frac{y_j - \hat{y}_j}{y_j}\right|. \tag{10}$$

Here the MAPE in equation (10) is computed over m forecasted data points. This metric provides us an indicator of periods when "forecast failure" happens, such as when corporate actions, take an example like MSTR's leverage plans, causing the stock to temporarily deviate from its historical BTC-beta.

The implementation of specific logic above, which is performed by the iterative update of regression coefficients and the computation of the sequence of 1-step forward forecasts of $\{\hat{y}_j\}_{j=k_0+1}^{N}$, is formalized in Algorithm 1 and Algorithm 2.

4. Results and Discussion

4.1 Micro Strategy (MSTR)

Here we present the result of MSTR price forecasting based on BTC price. When we plot the MSTR price along BTC price on the same horizontal (date) axis, we can see obvious correlated pattern visually apparent, as seen in Figure 2.

This apparent correlated prices between MSTR and BTC can be shown as almost-linear relationship. The scatter plot along with the regression line is plotted in Figure 3, which confirm our observation, that both prices strongly correlated with correlation coefficient/determination, r^2 = 0.86992.

The result of 1-step forecast using rolling growing-window-size linear regression is shown on Figure 4, here the forecasted values are close enough to the actual values, except that from March 2024 until May 2025, the forecasted values are less than actual values. This forecast has Mean Absolute Percentage Error, MAPE = 0.216986258.

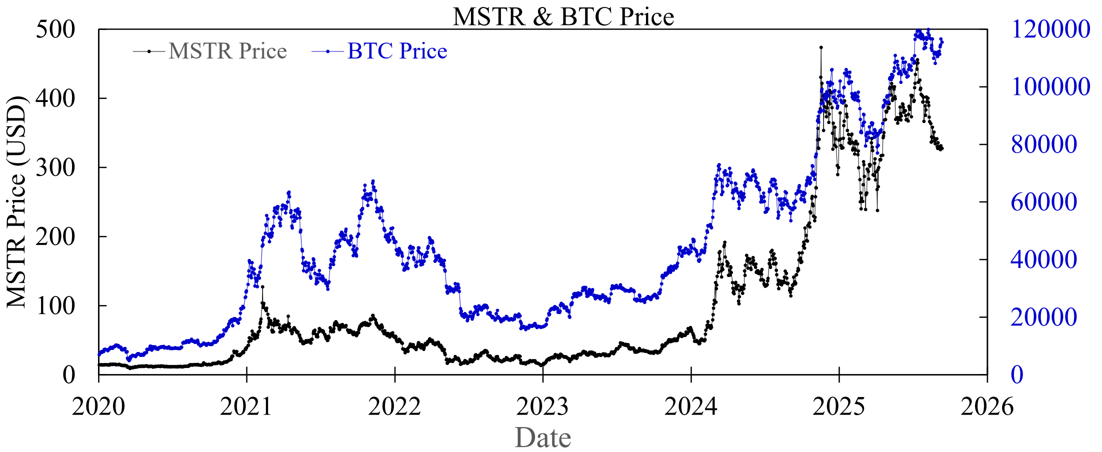

Figure 2. MSTR and BTC closing prices in USD. The left and right vertical axes correspond to MSTR and BTC prices, respectively.

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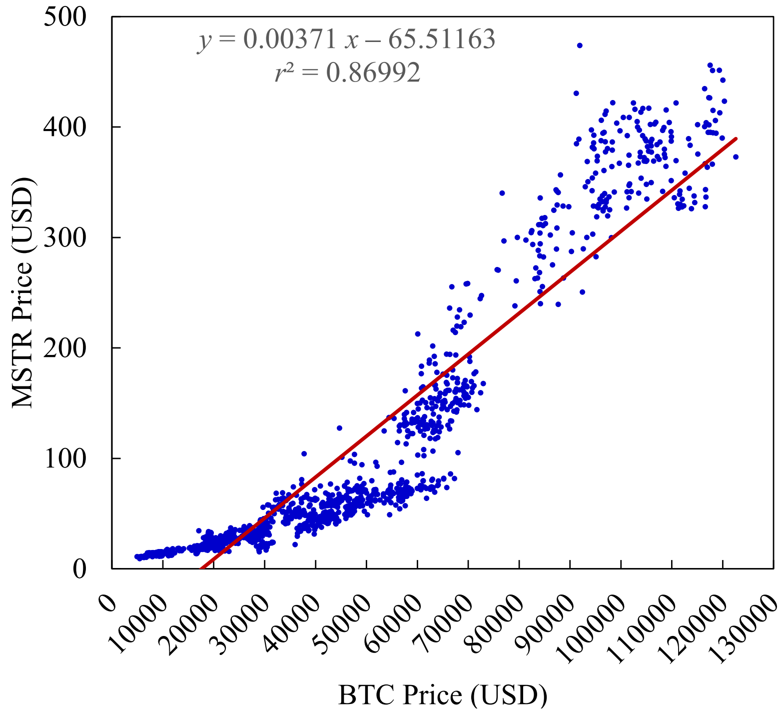

Figure 3. Almost-linear relationship of MSTR price and BTC price. The regression line is plotted in red.

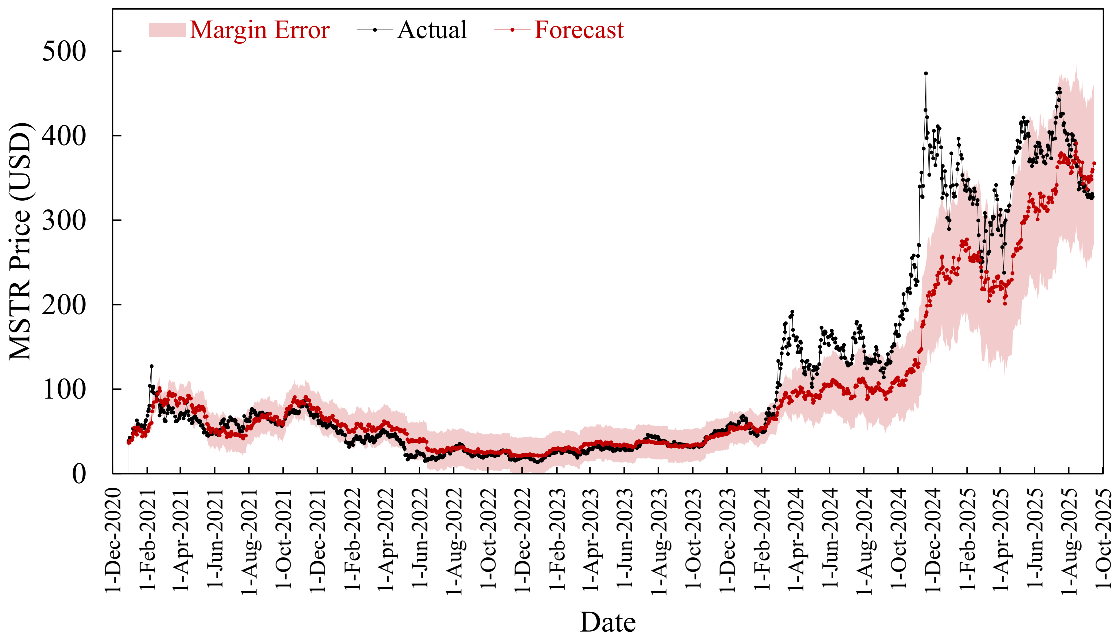

Figure 4. The 1-step forecast using rolling growing-window-size linear regression, with MAPE = 0.216986258. Forecast of MSTR price (red) with margin error (pink shade), alongside with actual MSTR price (black).

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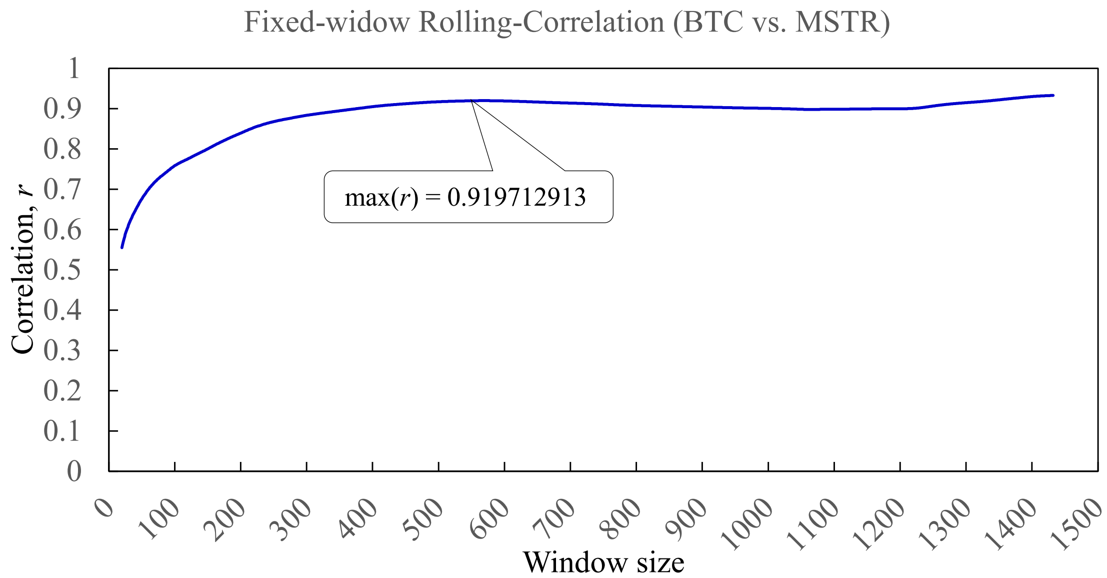

Figure 5. The average values of fixed-window (MSTR vs. BTC) rolling correlation vs. their corresponding window-size. The maximum correlation, max(r) = 0.919712913 when window-size is k_0 = 569.

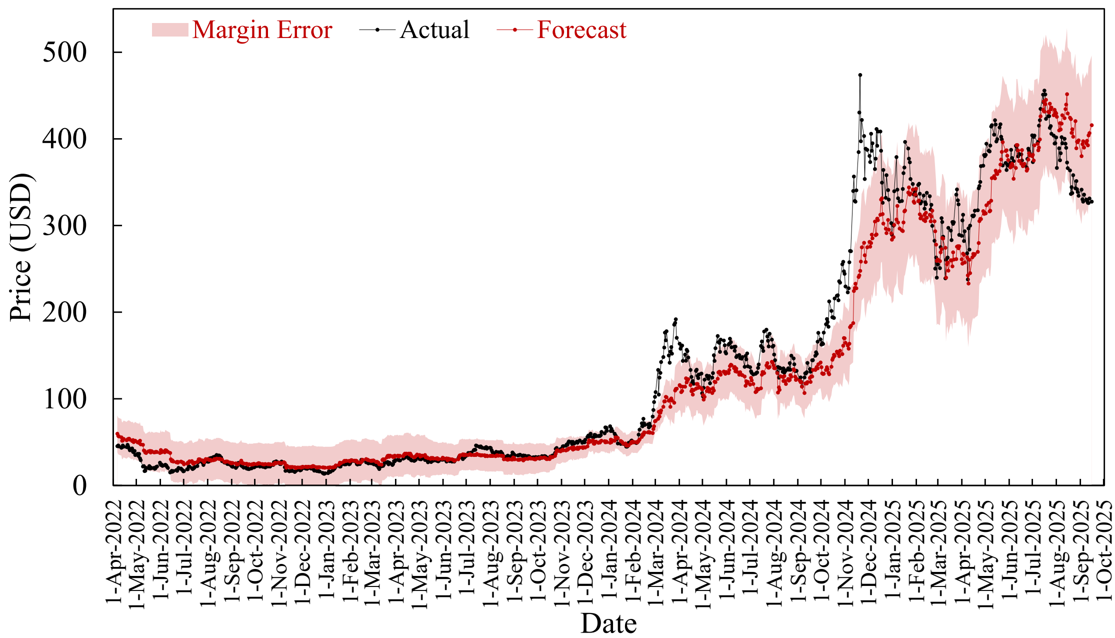

Figure 6. The 1-step forecast using rolling fixed-window-size, k_0 = 569, linear regression, with MAPE = 0.173126938. Forecast of MSTR price (red) with margin error (pink shade), alongside with actual MSTR price (black).

The result of 1-step forecast using rolling fixed-window-size linear regression is shown on Figure 6, where the window size is fixed using the value of k_0 = 569, at which, the calculated correlation coefficient is maximum. Note that chosen value here is taken in the first half interval of the whole dataset range, that is, $k_0 < N/2$, so that the window size is not too large. Here, the forecasted values are close enough to the actual values, except that from March 2024 until Dec 2024, the forecasted values are less than actual values, however, this interval is shrinking compared to growing-window-size, which

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means better result, that is also indicates by the value of MAPE=0.173126938, lower than MAPE value of growing-window-size.

Looking more closely at the differences between the forecasts in Figure 4 and Figure 6 show that they are not just random numbers. Instead, they are the numeric effects of MicroStrategy's (MSTR) major change into a "leveraged call option" on Bitcoin. The models try to fit a straight line relationship, but the real price history of MSTR in late 2024 and early 2025 was caused by non-straightline corporate actions, like aggressive borrowing and strategic capital raises, that broke the historical linearly correlation patterns.

Figure 4 shows that a “growing-window” Rolling Linear Regression (RLR) model has a big "lag" or under-forecasting bias during the huge rise in late 2024. This mistake is caused by the model's memory. With data going all the way back to 2020, the growing window "anchors" the prediction to a time when MicroStrategy was a more traditional software company and Bitcoin beta was smaller.

But in October 2024, a very important "decoupling" event took place. Bitcoin prices stayed pretty steady while MSTR stock went up about 18% in just a few days. This happened because the "21/21 Plan" was made public. It is a bold plan to get $42 billion in capital ($21 billion in stock and $21 billion in fixed income) to buy more Bitcoin quickly. A straight line model based on past Bitcoin correlations would not be able to explain this corporate-specific trigger. The model thought that MSTR would move along with BTC, but MSTR was actually moving based on its own aggressive treasury expansion. This meant that the forecasts was much lower than the real explosive growth.

Figure 6 fixed some of the "anchoring" bias by using a "fixed-window" (about 1.5 years), but it also added a new error: "overshooting during reversals.", hence, high volatility. By the end of 2025, the relationship had turned around. The premium fell after months of trade at a huge premium to its Net Asset Value (NAV), which sometimes reached 2x or 3x the value of its Bitcoin holdings. The stock experienced laverage trap and reversal. Therefore, the MAPE=0.173126938 here is better than of Figure 4, MAPE = 0.216986258.

The main reason why the forecasts are inaccurate at that is that MSTR is a "convex instrument." Bitcoin doesn't move in a straight line; it speeds up. The 10-for-1 stock split on August 2024 boosted retail liquidity and speculative fervor, which caused volatility that wasn't caused by Bitcoin's price change.

By releasing billions of dollars in convertible notes, like in September and November 2024, MicroStrategy used its balance sheet to get more money. This kind of leverage really speeds up the stock price during a bull market, much higher than what a straight line Bitcoin connection would suggest. During a downturn, it holds the price down and makes it fall faster than the core asset.

In short, the window period of "inaccuracy" in the forecasts is actually a representation of the extra return (or loss) that Michael Saylor's capital markets plan creates that isn't caused by the simple price movement of Bitcoin. A linear regression model thinks this amount is "error," but it's really the premium (or discount) that investors give to MicroStrategy's ability to buy Bitcoin with cheap loans.

4.2 BlackRock (BLK)

Here we present the result of BLK price forecasting based on BTC price. When we plot the BLK price along BTC price on the same horizontal (date) axis, we can see obvious correlated pattern visually apparent, as seen in Figure 7.

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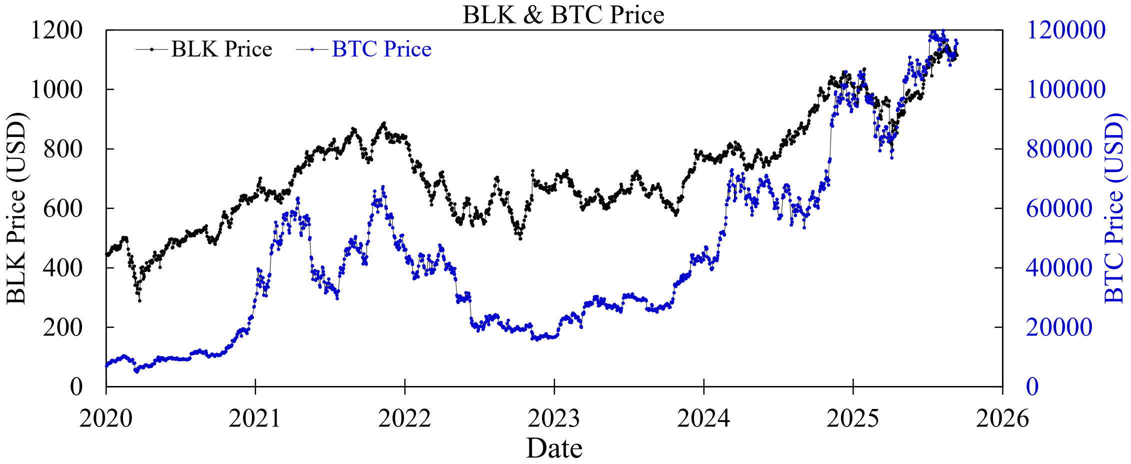

Figure 7. BLK and BTC closing prices in USD. The left and right vertical axes correspond to BLK and BTC prices, respectively.

This apparent correlated prices between BLK and BTC can be shown as almost-linear relationship. The scatter plot along with the regression line is plotted in Figure 8, which confirm our observation, that both prices strongly correlated with correlation coefficient/determination, $r^2 = 0.84139$.

The result of 1-step forecast using rolling growing-window-size linear regression is shown on Figure 9, here the forecasted values are close enough to the actual values. This forecast has MAPE = 0. 078851051.

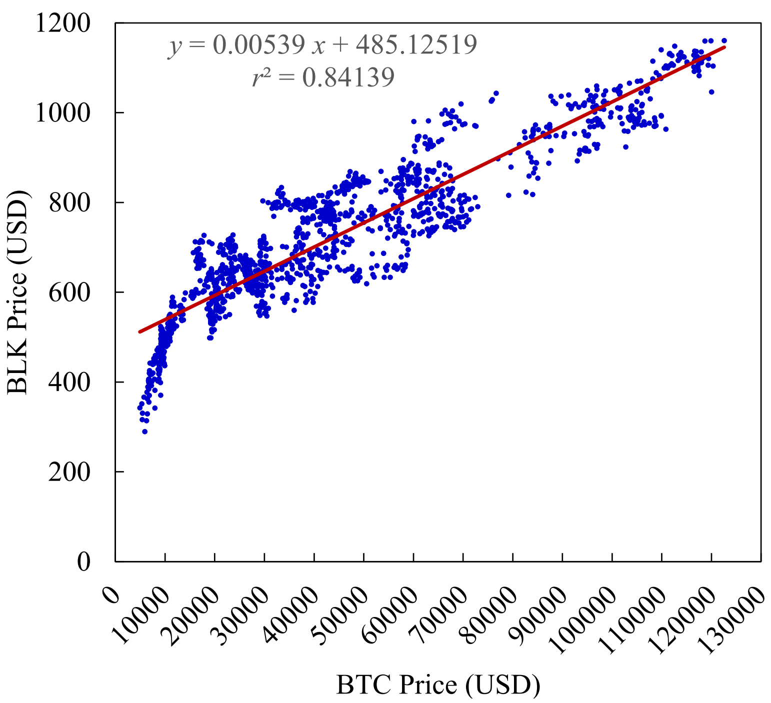

Figure 8. Almost-linear relationship of BLK price and BTC price. The regression line is plotted in red.

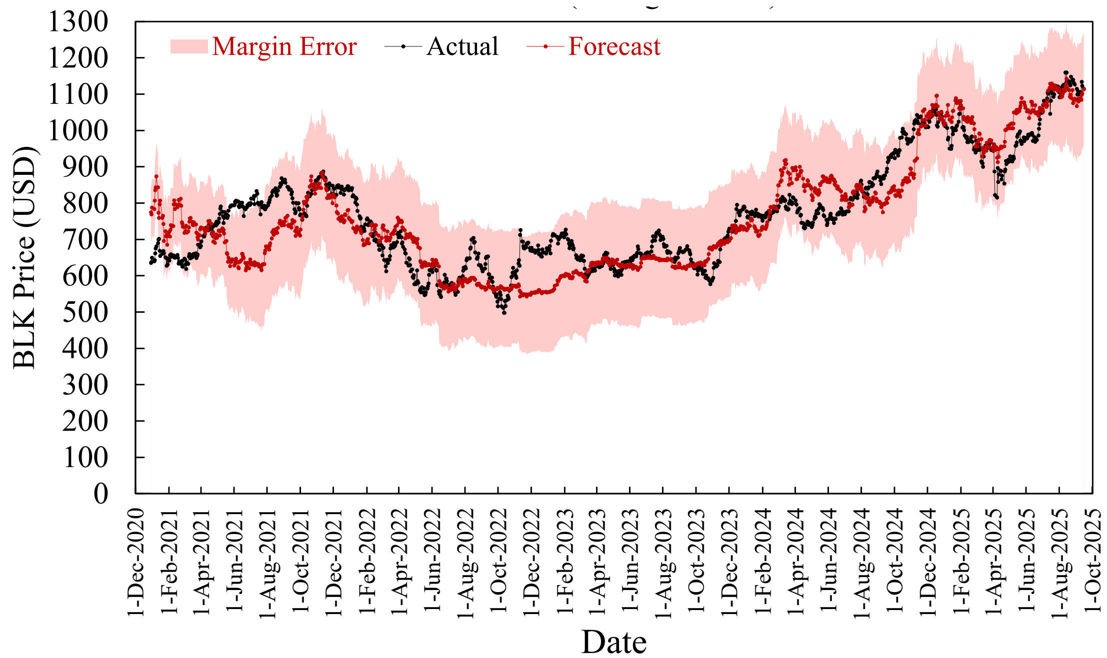

Figure 9. The 1-step forecast using rolling growing-window-size linear regression, with MAPE = 0. 078851051. Forecast of BLK price (red) with margin error (pink shade), alongside with actual BLK price (black).

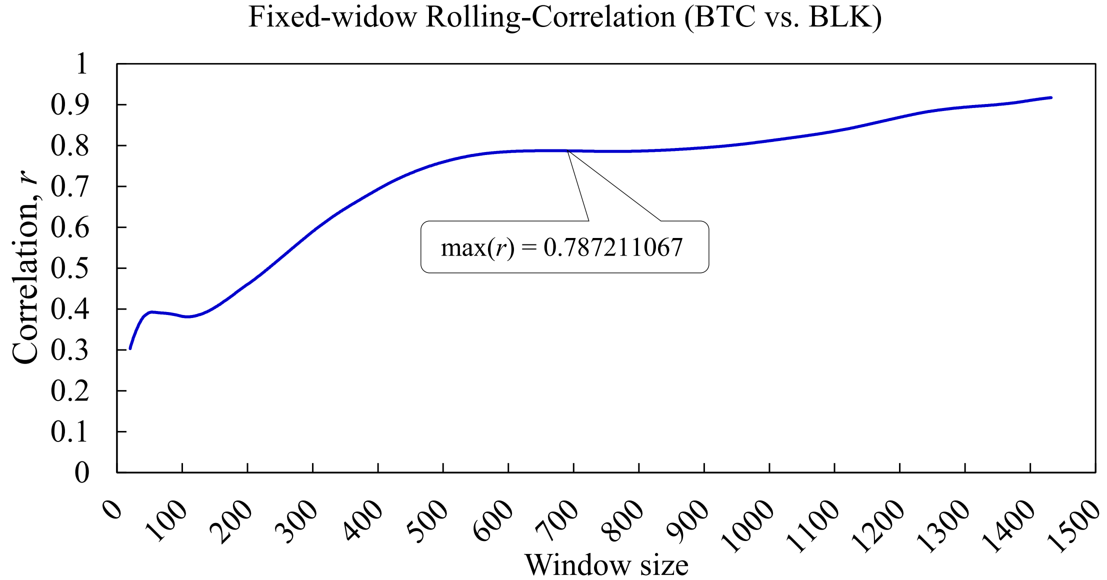

Figure 10. The average values of fixed-window (BLK vs. BTC) rolling correlation vs. their corresponding window-size. The maximum correlation, max(r) = 0.787211067 when window-size is k_0 = 664.

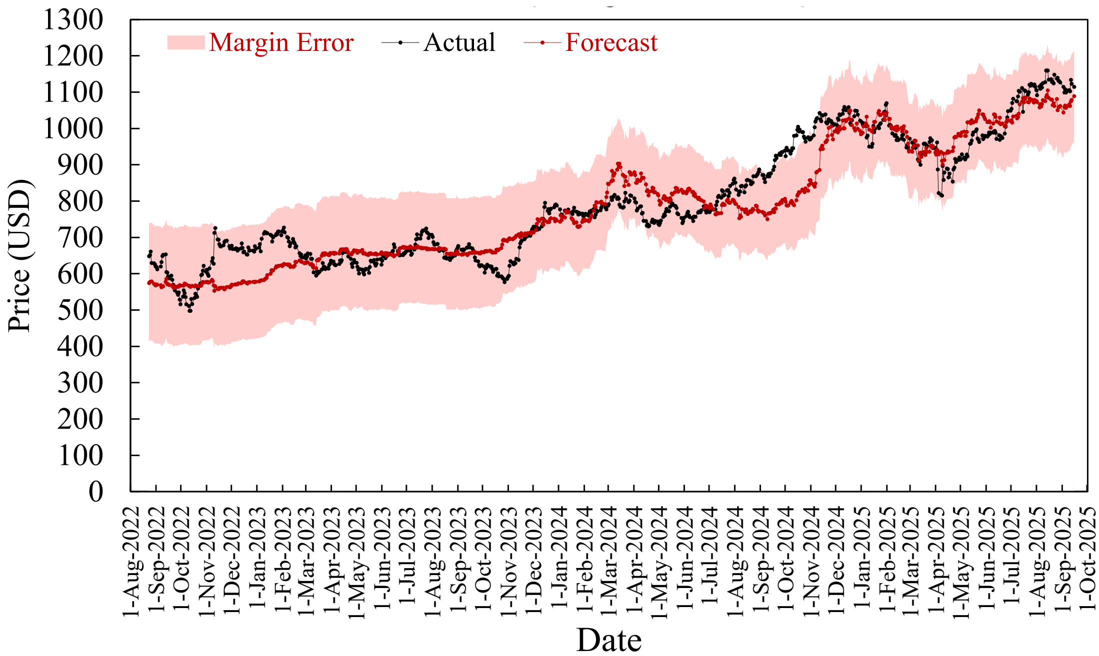

Figure 11. The 1-step forecast using rolling fixed-window-size, $k_0 = 664$, linear regression, with MAPE = 0.064145664. Forecast of BLK price (red) with margin error (pink shade), alongside with actual BLK price (black).

The result of 1-step forecast using rolling fixed-window-size linear regression is shown on Figure 11, where the window size is fixed using the value of $k_0 = 664$, at which, the calculated correlation coefficient is maximum. Note that chosen value here is taken in the first half interval of the whole dataset range, that is, $k_0 < N/2$, so that the window size is not too large. Here, the forecasted values are close enough to the actual values, with value of MAPE = 0.064145664, lower than MAPE value of growing-window-size.

4.3 Analysis and Discussion

The results of the Rolling Linear Regression (RLR) analysis give us a deep understanding of the "crypto-equity nexus" as it was until late 2025. When we compare MicroStrategy (MSTR) and BlackRock (BLK), we are not just looking at two different tickers; we are also looking at two different ways that digital asset volatility might affect the traditional equities markets. The data indicates that Bitcoin (BTC) serves as a principal factor in price discovery for equities; however, the fidelity, magnitude, and linearity of this transmission differ markedly according to corporate structure, particularly between a "active" leveraged balance sheet and a "passive" fee-generating entity.

The examination of MicroStrategy presents a persuasive account of structural evolution that contests the constraints of traditional linear modeling. The scatter plot shows an almost-linear relationship with a coefficient of determination r^2 of about 0.87, which makes it seem like it can make good predictions at first. However, a more thorough look at the forecast errors shows that utilizing MSTR as a proxy has its limits. The growing-window RLR model has a MAPE of about 21.7%, which shows that it was very biased in its predictions. The "anchoring" effect that comes with the growing-window strategy is mostly to blame for this comparatively inaccuracy rate. The model gave a lot of weight to a time when MicroStrategy mostly worked as a software company and had a smaller connection to digital assets by using data from 2020. As a result, the model didn't quickly adjust to the regime change that happened in late 2024, which led to a

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consistent under-forecasting of the stock price throughout the huge surge that followed the company's aggressive capital expansion.

After the "21/21 Plan" was announced in late 2024, this difference got much bigger. The plan was to raise $42 billion in funding to buy more Bitcoin. This action caused a "decoupling," which means that MSTR's stock price rose faster than the actual spot price of Bitcoin. The market started to value MSTR not only based on how much Bitcoin it currently holds, but also based on how much it could earn in the future through leveraged financing. The linear regression model viewed this premium, which typically traded at multiples of the Net Asset Value (NAV), as an error term instead of a basic valuation feature. This supports the idea that MSTR acts as a "convex instrument" or a leveraged call option, with a beta much larger than 1. Corporate measures, such the issue of convertible debt and the 10-for-1 stock split in August 2024, made the stock even more volatile. These operations added retail liquidity dynamics that were not related to Bitcoin's immediate price action.

To lessen the bias caused by historical data "anchoring," it was required to use a fixed-window RLR with a window size of k_0 = 569. This method made the forecast more accurate by lowering the MAPE to about 17.3%. The fixed-window methodology let the regression coefficients drift and adjust more quickly to the "crypto-beta" regime that defines modern MicroStrategy by getting rid of earlier, less relevant data. Still, even this improved model had trouble with "overshooting during reversals," which showed how volatile the stock's leverage trap dynamics are. This means that linear regression can show the general trend, but the relationship between MSTR and BTC is fundamentally recursive and leverage-amplified. This means that during bull markets, the stock's premium grows in a non-linear way, and during corrections, it shrinks sharply. This makes a volatility profile that a simple linear model has a hard time fully capturing without switching parameters.

The analysis of BlackRock (BLK) shows institutional stability and predictable transmission, which is very different from MicroStrategy's volatility and leverage dynamics. The association between BLK and BTC is a little less strong than the relationship between MSTR and BTC, with a r^{2} of about 0.84. However, it follows a considerably more straight path. The predicting performance for BlackRock was much better, with the growing-window model only giving a MAPE of about 7.9%. This level of accuracy shows that the association is "second-order." BlackRock's risk from Bitcoin is not directly on its balance sheet. Instead, it comes from the fees it makes from the iShares Bitcoin Trust (IBIT) and the "halo effect" of being the main institutional gateway to the digital economy.

The BlackRock model is even more stable because there isn't much difference between the growing-window and fixed-window methods. The fixed-window model, with k_0 = 664, did make the MAPE better, bringing it down to about 6.4%. However, this change was not as big as the one shown in the MicroStrategy analysis. This means that the structural link between BlackRock and Bitcoin stays rather consistent over time. BlackRock is still a diverse asset manager, but Bitcoin is a rising but limited variable. MicroStrategy, on the other hand, fundamentally changed its corporate DNA to become a Bitcoin treasury. The "spillover effect" seen here backs up what other research has said: traditional financial giants are becoming more sensitive to crypto-sentiment, but they are still safe from the unique liquidation risks that affect direct holders or leveraged companies.

Ultimately, the comparative examination of these two equities elucidates the trade-offs inherent in rolling linear regression approaches. The size of the window k is an important dial that controls bias and variation. For a stable, diverse organization such as BlackRock, an extended or expanding window is permissible and produces highly precise outcomes due to the relative constancy of the underlying parameter vector β. But for a dynamic, regime-shifting company like MicroStrategy, the idea that parameters stay the same is not true. The "boxcar" effect of the fixed window, while statistically inefficient in some settings, is necessary to capture the changing "premium dynamic" that Saylor's technique brings about. The data shows that linear regression is a strong tool for predicting the "passive" conduit (BLK). However, it only works as a baseline directional indicator for the "active" leveraged adopter (MSTR), where the company's aggressive capital market activities make price shocks harder to understand.

5. Conclusion

This study successfully characterizes the "crypto-equity nexus" as a bifurcated phenomenon, confirming that Bitcoin (BTC) is a primary and influential factor in the valuation of both MicroStrategy (MSTR) and BlackRock (BLK). The application of Rolling Linear Regression (RLR) analysis provides a detailed, time-varying assessment of the distinct transmission mechanisms, directly answering the research objective of analyzing correlations and forecasting stock prices based on BTC.

The key findings reveal a profound divergence shaped by corporate strategy. For MicroStrategy (MSTR), the relationship with BTC is non-linear and leverage-amplified. The stock acts as a high-beta, convex instrument, where its price incorporates a speculative premium driven by market sentiment and corporate debt strategy, as seen in its "21/21 Plan." This non-stationary relationship is evidenced by the superior performance of a short, fixed-window RLR over a growing-window model, indicating a significant "memory bias." MSTR's valuation behaves more like a leveraged call option on BTC, making it less predictable with standard linear models.

In sharp contrast, the relationship for BlackRock (BLK) is systematic and stable. Its connection to BTC is mediated through the fee-based success of its iShares Bitcoin Trust (IBIT), positioning the firm as a financial conduit. The RLR model demonstrated significant predictive accuracy for BLK, with both windowing methods performing well. This reflects the institutionalization of Bitcoin, where BLK's valuation responds linearly to the "spillover effect" of crypto market growth into traditional finance via steady fee revenue.

These results offer critical insights for theory and practice:

1) They challenge traditional valuation models, illustrating the emergence of a "Bitcoin-Standard" treasury archetype where capital structure directly amplifies market value.
2) They confirm the financialization of Bitcoin and the resulting reflexive feedback loops between asset prices and institutional adoption.
3) They highlight emerging systemic risks, as a pervasive "crypto-beta" compromises traditional diversification, necessitating updated risk management frameworks that account for cross-asset volatility spillovers.
4) They underscore the necessity of adaptive, non-stationary predictive modeling in rapidly evolving market nexuses, where the optimal forecasting window is itself a reflection of underlying corporate reality.

In conclusion, while BTC is a common determinant, the risk profile and optimal forecasting approach must be meticulously tailored based on whether an equity is an *active participant* (leveraged, high-beta) or a *passive facilitator* (fee-based, stable conduit) in the digital asset economy. This study bridges corporate finance and digital asset econometrics, providing a foundational pathway for modeling the integration of decentralized assets into centralized balance sheets. Future research should integrate corporate finance variables with non-linear or regime-switching models to better capture the leverage premium dynamics evident in active adopters like MicroStrategy.

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