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Valuing Digital Asset Treasury Companies: Integrating Augmented CAPM and Machine Learning in MicroStrategy

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Abstract. The integration of cryptocurrencies into corporate treasuries has created a new asset class of "Digital Asset Treasury" companies, its correlation with cryptocurrencies troubles traditional valuation frameworks. This study investigates the pricing mechanics of MicroStrategy as a case study, to determine whether its equity premium can be explained by standard market factors. Using daily data from 2020 to 2025, this study first identifies the return correlation between MSTR and BTC, which surged to $r = 0.695$ after BTC's appearance in its portfolio. This paper evaluates the limitations of the traditional Capital Asset Pricing Model (CAPM) and proposes an augmented CAPM incorporating a specific Bitcoin return factor. Linear regression results of the traditional model indicate that MSTR is a leveraged BTC proxy, while traditional CAPM only brings $R^2 = 21.8\%$ explanatory power. Furthermore, this study simulates the convexity of MSTR to BTC returns in extreme days using a non-linear function format. Finally, delivering enhancement for the model is necessary; thus, this study utilizes the Random Forest algorithm and SHAP analysis to rate all considered factors, and come up with a multi-factor, non-linear model specifically designed for the valuation of DAT companies.

Keywords: digital asset treasuries, Bitcoin, cryptocurrency, corporate finance, machine learning

1. Introduction

In recent years, digital assets, such as cryptocurrency and real-world-asset (RWA), led by Bitcoin, have transitioned from fringe investments to mainstream consideration, exerting a profound impact on traditional financial markets. Outstandingly, the pioneers of listed companies, started to allocate capital to Bitcoin within their portfolios. Therefore, research on these companies expands substantially across both academic and industry domains. Krause indicates that, volatility of stock prices of DAT (digital asset treasury) companies has a greater beta over 1.0 than others [1]. Hannah Lang also indicates that some companies are trying to expand towards more exotic and less liquid cryptocurrencies, bringing more volatility and uncertainty to their stock price [2].

MicroStrategy (Nasdaq: MSTR), once a traditional business intelligence firm, has become the leading example of the corporate shift toward crypto-treasury strategies. Since adopting Bitcoin (BTC) as its primary reserve asset in August 2020, the firm has fundamentally reshaped its risk profile. This transformation challenges conventional asset-pricing logic: standard CAPM

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frameworks, which assume market-beta-driven operating firms, struggle to capture the heightened and leveraged volatility characteristics of a company whose equity effectively behaves as a crypto-exposure vehicle.

This study critically evaluates the applicability of the traditional CAPM in analyzing DAT companies, using MicroStrategy as a prime case study. Firstly, a correlation verification between BTC and MSTR returns to establish the structural break in the asset's behavior following its BTC buying plan. Subsequently, we test the limitations of the traditional CAPM and propose an augmented model incorporating a specific BTC return factor. Finally, extending beyond linear regression, this research utilizes machine learning techniques, the Random Forest algorithm and SHAP analysis to quantify the contribution of every considered factor. The study proposes a multi-factor, non-linear asset pricing specifically suitable for the valuation of DAT companies.

2. Traditional CAPM model applying to DAT companies

2.1. Data collection

Strategy (formerly MicroStrategy) is a publicly listed firm in the United States, whereas Bitcoin is a decentralized digital asset traded on various cryptocurrency exchange platforms. To maintain consistency in data structure and cross-asset comparability, this study obtains all price series from a unified source—Yahoo Finance.

Market data were collected from the Fama-French official website.

2.2. Verification of price correlation between BTC and MSTR

Recent empirical studies reveal the co-movements between the two assets. For instance, analysis from Phillips documents that the Pearson correlation coefficient between MSTR and BTC returns has remained around 0.6851 [3], showing high-level correlation. Moreover, studies of S. Aufiero, et al quantify the nonlinear directional information flow using Transfer Entropy to identify the leading source of price fluctuations [4].

To qualify the correlation of BTC returns and MSTR returns before and after the announcement of buying Bitcoin, the study computes a Pearson correlation coefficient of their daily returns over the period (2015/06/08-2020/07/28) and (2020/08/11-2025/09/30).

Figure 1 visually illustrates the structural break in the dependency between MSTR performance and BTC returns. The left panel depicts a cloud-like distribution near a near-flat line, with a negligible $r = 0.057$. In stark contrast, the right panel shows data points tightly clustering around a steeply-upward regression line, indicating that through the whole period of 2020-2025, MSTR returns have a robust linear relationship between BTC returns and itself. The correlation coefficient surges to $r = 0.695$ and p-value collapses to vanishingly small as $p \approx 0$, confirming that after Bitcoin's appearance in MicroStrategy's portfolio, the company has become a proxy for enjoying the risk exposure of Bitcoin.

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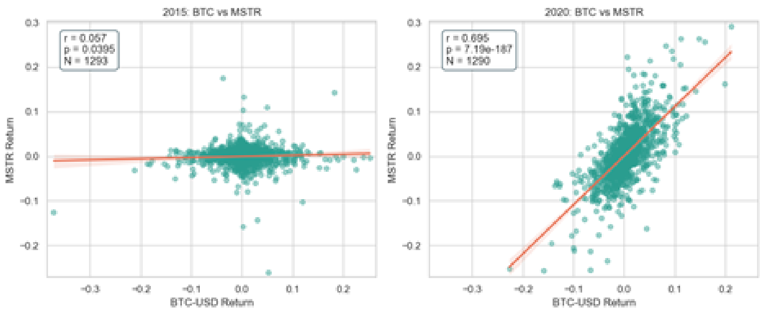

Figure 1. Regime shift in MSTR returns-BTC returns

2.3. Performance of traditional model

Capital assets pricing model, also CAPM, has been applied to deliver analysis on return of specific asset. Kwamie Dunbar and Johnson Owusu-Amoako conducted a study, investigating the predictability of cryptocurrency returns through the lens of empirical asset pricing models. Their findings demonstrate that the cryptocurrency market risk premium is a robust predictor of returns [5]. By the same logic, it can be inferred that MSTR, which is highly correlated with BTC, also fits within similar hypothesis.

To establish the benchmark of CAPM, this study firstly employs the classical model to MSTR:

$$R_i = R_f + \beta_m (R_m - R_f) \tag{1}$$

The formula is processed into the following format while regressing, Table 1 and Figure 2 show an suboptimal outcome produced after given data from 2020.

$$R_i - R_f = \alpha + \beta_m (R_m - R_f) + \varepsilon \tag{2}$$

Table 1. Results of single factor linear regression

Variables	Coefficient	HAC Std. Error	z-Statistics	p-Value
α	0.0028	0.001	1.920	0.055
β_m	3.0026	0.199	15.067	0.000
R^2	0.218			
F	227.0			

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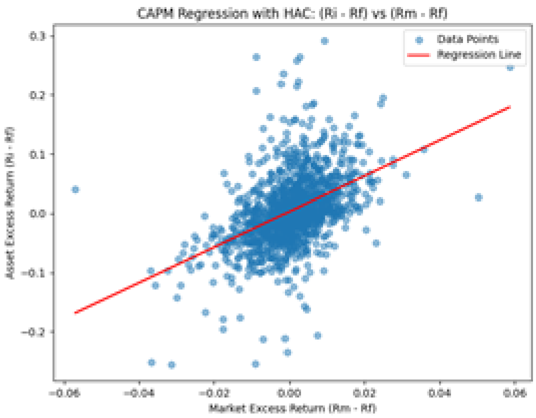

Figure 2. Results of traditional CAPM

The results, as reported in Table 1 and Figure 2, demonstrate that with $a\beta_m = 3.0026$, MSTR is a high-beta stock whose excess returns are extremely sensitive to aggregate equity market movements. The estimated daily alpha of 0.28% is only marginally significant at the 10% level ($p = 0.055$), providing limited evidence of abnormal performance beyond market exposure. The CAPM specification explains about 21.8% of the variation in MSTR's daily excess returns ($R^2 = 0.218$), with the overall regression being highly significant ($F = 227.0$, $p < 0.001$).

2.4. Comparison to other companies

In the general classification system, MicroStrategy engages in both technology sector and finance sector, in attempt to conduct lateral comparison between MicroStrategy and its fellows, several market-value-leading corporations are selected for contradistinction. Results are displayed in Table 2 and Table 3.

Table 2. CAPM applied to technology companies

Variables	R^2	α	p_α	β	p_β	F _ Statistics
MSTR	0.218	0.0028	0.055	3.0026	0.000	227.0
AAPL	0.470	0.0001	0.723	1.3676	0.000	1143.0
AMD	0.396	0.0001	0.941	2.1530	0.000	842.7
MSFT	0.478	0.0002	0.502	1.2395	0.000	1181.0
NVDA	0.425	0.0016	0.018	2.3226	0.000	952.2
ORCL	0.207	0.0009	0.105	1.1439	0.000	335.5

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Table 3. CAPM applied to finance service companies

Variables	R^2	α	p_α	β	p_β	F _ Statistics
MSTR	0.218	0.0028	0.055	3.0026	0.000	227.0
BAC	0.376	0.0000	0.900	1.1797	0.000	775.8
GS	0.469	0.0005	0.139	1.2864	0.000	1137.0
JPM	0.369	0.0004	0.223	1.0496	0.000	754.8
MA	0.460	0.0001	0.868	1.1616	0.000	1096.0
MS	0.476	0.0003	0.344	1.3560	0.000	1171.0
V	0.422	0.0001	0.959	1.0174	0.000	939.8

Compared to most other analyzed technological companies and finance service companies, whose CAPM estimations typically exhibit R2 values in the range of approximately 0.36 to 0.48. However, MSTR's substantially lower R-square suggests that the traditional CAPM explains far less of the variation in its returns. Moreover, the p-value associated with MSTR's alpha ($p = 0.055$) lies merely slightly above the significance threshold, indicating that unexplainable MSTR returns produced by CAPM aren't completely negligible.

3. Refinement of the model in MSTR case

3.1. Examination and period separation

Sandro C. Andrade, Brian Coomes and Diogo Duarte reports that under "Hype State" [6], MSTR's stock price can be dissembled into two parts: its intrinsic value and premium, even violating Modigliani-Miller condition. Patrick Bush also indicates that the premium appears as investors' optimism attitude to Bitcoin's future and proxy of legitimation pathway [7]. Generally speaking, both BTC returns and market consensus or sentiment have a strong impact on MSTR performance, therefore, 2020/08/11-2025/09/30 is separated into an optimistic period and pessimistic period.

Researchers have proposed numerous approaches to determine market regimes, for instance, Jeremy Siegel investigates the use of 200-day moving average, and documents that conducting selling when the price drops below MA200 can reduce portfolio maximum drawdown [8]. Glabadanidis conceptualizes moving average strategy as dynamic asset allocation, with Strub and Issam S introducing extreme value theory, and empirically proving its returns are distributed as a protective put option [9,10].

To simplify the regime-classification rule of this study, a criterion based on "MA200" is adopted. US stock trading days are classified as bullish when the spot Bitcoin price isn't lower than MA200, otherwise as bearish.

Table 4. Correlation coefficients against MSTR vary in bearish and bullish markets

Variables	R^2	α	p_α	β	p_β	F _ Statistics	N
Bullish	0.118	0.0040	0.032	2.6981	0.000	113.0	840
Bearish	0.374	0.0014	0.550	3.1977	0.000	119.4	450

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Regression analysis for each case is done, and its results are shown in Table 4. R^2 significantly vary in the bullish and bearish cases; furthermore, α, p_α of bearish case can be interpreted as insignificant unexplained return while in the bullish case it's not negligible. Overall, the single-market-factor CAPM model fits bearish circumstances better.

3.2. Considering BTC returns factor

As mentioned, MSTR returns have been highly correlated with BTC returns in the past 5 years, considering the inclusion of BTC return factor into CAPM formula is warranted. A linear term for BTC returns is added.

$$R_i - R_f = \alpha + \beta_m (R_m - R_f) + \beta_{BTC} (R_{BTC} - R_i) + \varepsilon \tag{3}$$

Table 5. Regression analysis of adjusted CAPM adding linear term of BTC returns

Variables	R^2	α	p_α	β_m	p_{β_m}	β_{BTC}	$p_{\beta_{BTC}}$	F _ Statistics
Bullish	0.466	0.0001	0.935	1.4677	0.000	0.9707	0.000	165.5
Bearish	0.647	0.0033	0.066	1.7136	0.000	0.9439	0.000	177.8

In the bullish case, compared to Table 4, R^2 in Table 5 has risen by 0.346 since adding a linear BTC factor term into the formula, while the intercept remains indistinguishable from 0. In the bearish regime, the same specification delivers an even higher explanatory power ($R^2 = 0.647$) and similarly indistinguishable intercept from 0, with an unexpectedly even larger market beta than that in the bullish regime.

In a bullish market, investors' enthusiasm often pushes the stock price higher than its intrinsic value, its power enhanced as price changes faster, and may somehow accelerate rather than rise linearly. Thus, this study proposes to add a square term of BTC excess return to the formula; however, the sign of each return has been preserved, meaning that negative returns are treated as negative values.

$$R_i - R_f = \alpha + \beta_m (R_m - R_f) + \beta_{BTC} (R_{BTC} - R_f) + \beta_{BTCSQ} (R_{BTC} - R_f)^2 + \varepsilon \tag{4}$$

Table 6. Results of BTC square term added model

Panel A: Model Statistics and Market Factors						
Variables	R^2	α	p_α	β_m	p_{β_m}	F _ Statistics
Bullish	0.466	0.0053	0.000	1.4586	0.000	123.6
Bearish	0.647	0.0004	0.817	1.7114	0.000	122.3
Panel B: BTC Factors						

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Table 6. (continued)

Variables	β_{BTC}	$p_{\beta_{BTC}}$	β_{BTCSQ}	$p_{\beta_{BTCSQ}}$
Bullish	0.9959	0.000	-0.3116	0.807
Bearish	0.9629	0.000	-0.2097	0.803

Results of adding a square term of BTC excess return are shown in Table 6 above, unlike what's expected, β_{BTCSQ} cannot simulate the convexity as MSTR performs in extreme positive days. To better simulate the convexity of MSTR-BTC, a replacement inspired by Taylor expansion is computed:

$$e^{x} - 1 - x \approx \frac{1}{2}x^{2} \tag{5}$$

$$R_i - R_f = \alpha + \beta_m (R_m - R_f) + \beta_{BTC} (R_{BTC} - R_f) + \beta_{NL} \left(e^{R_{BTC} - R_f} - 1 - R_{BTC} - R_f\right) + \varepsilon \tag{6}$$

Table 7. Results of BTC exponential term added model

Panel A: Model Statistics and Market Factors

Variables	R^2	α	p_α	β_m	p_{β_m}	F _ Statistics
Bullish	0.470	-0.0015	0.259	1.5377	0.000	129.4
Bearish	0.648	0.0023	0.159	1.7170	0.000	121.9

Panel B: BTC Factors

Variables	β_{BTC}	$p_{\beta_{BTC}}$	β_{NL}	$p_{\beta_{NL}}$
Bullish	0.9221	0.000	2.4049	0.066
Bearish	0.9577	0.000	1.1413	0.493

The results along with the former square term model reveal a special characteristic of MSTR's convexity, which is that the non-linear premium of MSTR does not originate from symmetric BTC volatility exposure, but rather from the "exponential explosiveness" exhibited during extreme Bitcoin rallies—a quintessential example of asymmetric right-tail risk pricing.

3.3. Rating all possible factors

Gu, S., et al. report that, utilization of machine learning forecast captures underlying non-linear correlation, which linear regression cannot capture [11]. Xuan, Z. applies SHAP analysis in ranking feature importance, enabling predictors extra explanatory power, and proposing a feasible method of applying machine learning in financial analysis [12]. Specifically, in the following discussion, this study selects a series of factors engaging numerous aspects, including fundamental drivers (Bitcoin

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returns and market factor), sentimental drivers (Google trend and fear and greed index), volatility power (liquidation momentum), and market analysis factor (SMB and HML) from the Fama-French model.

In the bearish case, this study has achieved a powerful explanatory fitness, however, the study still hasn't composed a robust formula for the bullish case. Before interpreting the feature contributions, this study first evaluates the predictive power of the Random Forest algorithm, which aggregates the predictions from an ensemble of independent decision trees to derive the model's R^2 by calculating the proportion of variance in the observed data that is explained by this collective average prediction. Random Forest algorithm explains MSTR returns by capturing non-linear dependencies and complex interactions between Bitcoin fundamentals and market microstructure, which traditional linear models fail to detect.

This study utilizes the former 80% bullish data for the training set, and the last 20% bullish data for the testing set. The total number of decision trees is set to be 200 and the maximum depth of each tree is set at 6 to avoid possible overfitting. Results of Random Forest analysis on bullish dataset suggest a robust predictivity, whose $R^2 = 0.590$, achieving a significant improvement compared to the exponential model's $R^2 = 0.470$. Moreover, this huge improvement indicates that previously undetected non-linear relationships and interactions between factors significantly affect the model's explanatory power.

Constructing an algebraic analytical expression for MSTR's return is necessary, since Random Forest demonstrates that by explaining MSTR's return by an ensemble of decision trees, providing a non-algebraic black-box. To interpret this non-parametric model and quantify how each factor influences the model, this study integrates SHAP (SHapley Additive exPlanations) values based on cooperative game theory. SHAP analysis visualizes how a specific factor exactly affects the model's outcome through visualization layouts. SHAP assigns a value to each feature representing its marginal contribution to the model's prediction, averaged over all possible combinations:

$$\phi_i = \Sigma_{S\subseteq F\setminus\{i\}} \frac{|S|!(|F|-|S|-1)!}{|F|!} \left[f\left(S \cup \{i\}\right) - f\left(S\right)\right] \tag{7}$$

Figure 3 displays SHAP summary plot resulting from the analysis. Among all the factors selected and constructed, BTC excess return carries the most weight of 51.71%, and its plot depicts a linear relation between SHAP value and itself, indicating that BTC excess return linearly affects MSTR return. Following this, the traditional market excess return (Mkt_ex) ranks as the second most weighted factor, contributing 16.07% to the model's explanatory power. Similar to the Bitcoin factor, the dependence plot for Mkt_ex exhibits a distinct positive linear trajectory, demonstrating that despite MicroStrategy has become a digital asset treasury company, its equity performance remains significantly tethered to broader systemic market risks and follows a traditional beta structure.

Convexity is decomposed as $e^{R_{BTC}-R_f}$ in the former chapters, this factor holds a substantial relative weight of 15.55%. Unlike the linear dependencies like BTC excess return, this factor shows a "hockey stick" shape distribution, indicating that in normal market conditions, the premium is minimal and insignificant. Nevertheless, as the extreme positive Bitcoin returns appear, the SHAP value surges rapidly, supporting the former convexity hypothesis and "Right-Tail Risk Pricing" hypothesis.

Additionally, five factors with lower weights have their own correlation with the model's explanatory power. The SMB factor shows a linear trend (3.46%), revealing that MSTR still stays significantly identical with small market cap companies. The HML (1.59%) factor is also from the

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Fama-French model, exhibits a negative near-linear relation between its SHAP value and itself. Volatility factor weighs at about 5.87%, indicating that MSTR tends to be overpriced once the volatility surges, showing the feature of an option. Fear and Greed value (2.54%) as well as Google trend of MSTR (3.21%) demonstrate sentimental factors conduct impact that cannot be ignored on the model's explanatory power; however, combined with their visualization outcome, neither a linear nor a simple non-linear relation between their SHAP values and themselves is displayed.

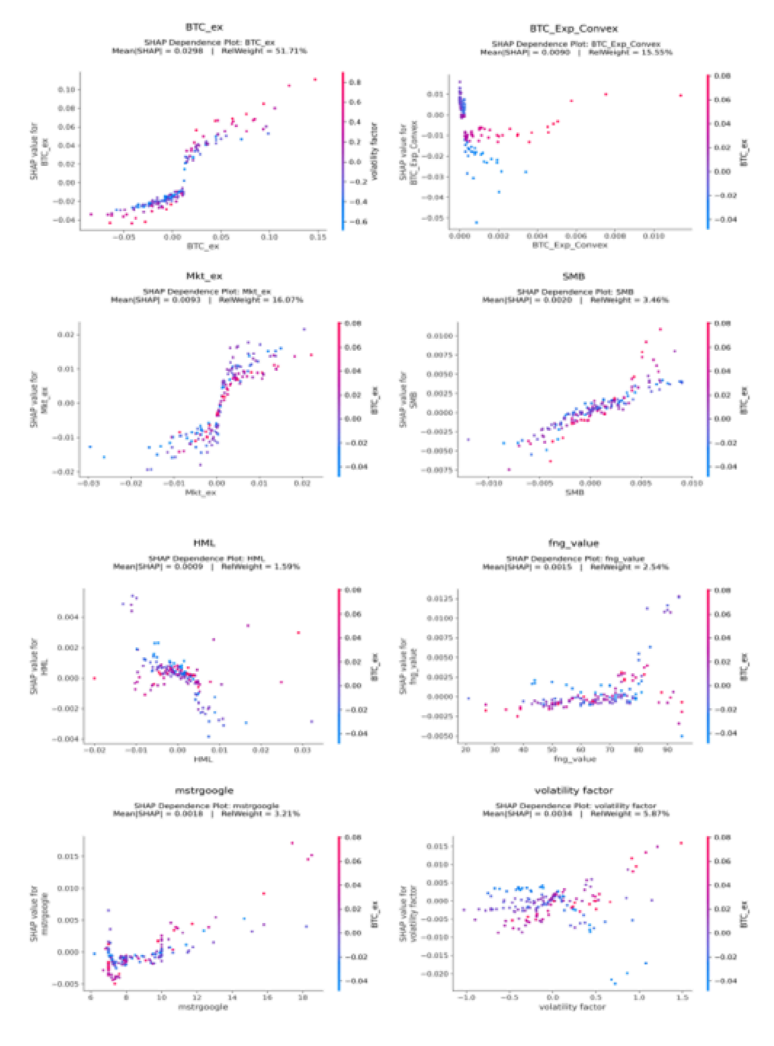

Figure 3. SHAP values of selected factors

3.4. Further enhancement of the model

To mitigate latent multicollinearity, we first introduced the SMB and HML factors, which exhibit a high degree of orthogonality to the crypto factors. The results are shown in Table 8:

$$R_i - R_f = \alpha + \beta_m(R_m - R_f) + \beta_{BTC}(R_{BTC} - R_f) + \beta_{NL} \tag{8}$$

$$(e^{R_{BTC}-R_f} - 1 - R_{BTC} - R_f) + \beta_{SMB}SMB + \beta_{HML}HML + \varepsilon$$

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Table 8. Results of augmented exponential model with FF3 factors

Panel A: Model Statistics and Market Factors

Variables	R^2	α	p_α	β_m	p_{β_m}	$F\_Statistics$
Bullish	0.481	-0.0009	0.494	1.5186	0.000	89.74
Bearish	0.665	0.0032	0.050	1.3926	0.000	79.96

Panel B: BTC Factors

Variables	β_{BTC}	$p_{\beta_{BTC}}$	β_{NL}	$p_{\beta_{NL}}$	β_{SMB}	$p_{\beta_{SMB}}$	β_{HML}	$p_{\beta_{HML}}$
Bullish	0.9114	0.000	2.3289	0.076	1.3810	0.001	-0.5514	0.039
Bearish	0.9313	0.000	0.6842	0.693	-0.2295	0.593	-1.2245	0.000

Powered by the Fama-French model, the explanatory power of the model on both bullish and bearish cases has slightly increased. SMB and HML factor exhibit as a significant influencer though carrying 5.05% SHAP weight in total. The significance of SMB indicates that MSTR performs as a small-cap characteristic, while the negative correlation of HML depicts MSTR's performance as a growth characteristic.

As Figure 3 mentioned, the fear and greed index is a proxy of the sentiment market factor and it carries a 2.54% weight. It clearly reflects the market's enthusiasm for paying a premium; to capture the convexity, this study adds one additional factor into the model, constructing a cross-term with the exponential term of Bitcoin excess return. Results are shown in Table 9.

$$\begin{aligned} \mathrm{R_i} - \mathrm{R_f} = {} & \alpha + \beta_{\mathrm{m}}(\mathrm{R_m} - \mathrm{R_f}) + \beta_{\mathrm{BTC}}(\mathrm{R_{BTC}} - \mathrm{R_f}) + \beta_{\mathrm{NL}}\left(\mathrm{e}^{\mathrm{R_{BTC}} - \mathrm{R_f}} - 1 - \mathrm{R_{BTC}} - \mathrm{R_f}\right) \\ & \times \max(0, fng_{value} - 60) + \beta_{\mathrm{SMB}} SMB + \beta_{\mathrm{HML}} HML + \varepsilon \end{aligned} \tag{9}$$

Table 9. Results of the model with a cross-term

Panel A: Model Statistics and Market Factors

Variables	R^2	α	p_α	β_m	p_{β_m}	$F\_Statistics$
Bullish	0.481	-0.0004	0.744	1.4938	0.000	87.32
Bearish	0.665	0.0038	0.032	1.3812	0.000	132.3

Panel B: BTC Factors

Variables	β_{BTC}	$p_{\beta_{BTC}}$	β_{NL}	$p_{\beta_{NL}}$	β_{SMB}	$p_{\beta_{SMB}}$	β_{HML}	$p_{\beta_{HML}}$
Bullish	0.9249	0.000	0.1271	0.063	1.3507	0.001	-0.5910	0.026
Bearish	0.9212	0.000	-4.8267	0.000	-0.2579	0.546	-1.2491	0.000

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The significance of the convexity term increases after constructing a cross-term between the exponential term and the Fear and Greed value (specifically over 60). The robustness of the convexity term has been proved since it maintains marginal significance, and surprisingly by a large negative coefficient for β_{NL} this term interprets the phenomenon that in bearish cases, traders tend to short risky assets when a bounce happens. However, after adding a sentiment-based factor to the formula, the explanatory power of the model remains consistent, as (8) at the level of explaining 48.1% of bullish and 66.5% of bearish variance.

The linear term of Bitcoin excess return and the linear term of market excess return remain robust throughout the refinement process; therefore, constructing cross-term involving them is a suboptimal path; moreover, constructing cross-term over SMB and HML is also unfeasible since the style of stock is highly orthogonalized to the BTC factors. To avoid overfitting the model to MSTR, and to prevent lowering F-statistics by incorporating noise, this study adopts (9) as the final specification.

4. Conclusion

This study demonstrates the significant challenges faced by traditional CAPM when applied to cryptocurrency-exposed DAT companies, as exemplified by MicroStrategy (MSTR). This study first conducts an empirical analysis and reveals that MSTR returns have become fundamentally affected by Bitcoin returns after 2020. Following this, traditional single-market-factor CAPM interprets MSTR as a high-beta stock with a $R^2 = 21.8\%$, significantly underperforming compared to benchmarks in the technology and financial sectors. To improve the explanatory power, this study firstly separates the dataset into bullish periods and bearish periods, acquiring 11.8% of variance explained in the bullish regime and 37.4% in the bearish regime. Furthermore, the linear term of BTC return is added into the regression formula (3), and the inclusion of a linear Bitcoin return factor significantly improves explanatory power to 46.6% in bullish regimes and 64.7% in bearish regimes.

To capture the premium that occurs when the market is in an over-enthusiastic condition, the square term of Bitcoin excess return with its original signal and the exponential Bitcoin excess return term are tested. The yield of the former one remains consistent with the linear model as (3); however, the latter one establishes a slight refinement involving an exponential term, explaining 46.7% variance in the bullish regime with a marginally significant β_{NL} (non-linear beta), and 64.8% in the bearish regime. Random Forest and SHAP analysis are utilized to simulate the optimal explanatory power considering economically meaningless interactions between the factors, and to rate all the selected factors. Guided by machine learning and the FF3 model, this study proposes the final specification (9), obtaining 48.1% explanatory power in the bullish regime and 66.5% in the bearish regime.

This study reveals MicroStrategy's "exponential convexity premium" relative to Bitcoin in bull markets, demonstrating the inadequacy of traditional linear valuation models. This provides a quantitative reference for market participants to conduct statistical arbitrage based on premium volatility and price deviation from prediction, while also alerting risk managers to employ non-linear hedging strategies against "right-tail risk" rather than simple linear approaches. However, limitations are significant: the single-case analysis lacks universality; the improved model's explanatory power remains below 50% in bullish regimes, implying substantial uncaptured noise.

Looking ahead, this study may be extended through several methodological enhancements. First, feature importance can be systematically assessed using both Gini Importance and Permutation Importance, thereby clarifying the relative contribution of each explanatory variable. In addition,

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multicollinearity diagnostics can be conducted through the calculation of Variance Inflation Factors (VIF) to ensure the statistical robustness of the regression framework. Furthermore, to refine model performance within a machine-learning context, more factors are to be mined and advanced algorithms such as XGBoost and LSTM may be incorporated, enabling the integration of nonlinear structures, temporal dynamics, and sentiment-driven reactions into the predictive system.

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