PREDICTING INTRADAY EQUITY RETURNS WITH BITCOIN OVERNIGHT INFORMATION

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Abstract: In our study, we investigate to what extent Bitcoin overnight returns contain relevant predictive information to predict the intraday direction of the returns of companies with direct exposure to the cryptocurrency ecosystem. The methodology involves the use of a Gaussian Process Regression on a single layer. The empirical determination of the results took into account limiting the main sources of overestimation of the model's performance, by strictly separating the training, validation and testing periods and avoiding look-ahead bias, but also data leakage. Furthermore, the research compares three investment mechanisms built on the same predictions generated by the model. The results aim to highlight that the economic value of predictive information depends not only on the statistical accuracy of the model, but also on how the signals are transformed into investment decisions.

***Keywords*:** Machine learning, financial forecasting, asset pricing, Gaussian proceses regression, trading strategies

INTRODUCTION

The development of the cryptocurrency market has led to a growing interest in understanding the relationships between digital assets and traditional financial markets. Some research described Bitcoin as a relatively poorly integrated asset with conventional markets, highlighting the existence of reduced links or even the absence of significant contagion and risk transmission effects (Qarni et al., 2019; Trabelsi, 2018) However, as the cryptocurrency market matured either through the addition of institutional investors or the emergence of new products, it grew, and the literature began to highlight an intensification of the interdependencies between Bitcoin and traditional financial markets. In this regard, Matkovskyy and Jalan (2019) show that the launch of Bitcoin futures contracts was associated with an increase in contagion effects between financial markets and the cryptocurrency market. Moreover, Zhang et al. (2021) challenge the hypothesis of Bitcoin's detachment from the global financial system and identify evidence of the existence of risk transmission effects to stock, bond, currency and commodity markets, showing at the same time that the intensity of these relationships is dependent on the time being analyzed. However, further research suggests that this integration is not permanent, but varies depending on the economic and financial context, becoming significantly more pronounced in periods characterized by high uncertainty and systemic shocks, such as the COVID-19 pandemic (Elsayed et al., 2021; Jiang et al., 2022; Zha et al., 2023). Finally, we can argue that recent literature converges to the idea that the relationship between Bitcoin and traditional financial markets must be seen as dynamic and dependent on market conditions, which justifies the growing interest in investigating the predictive information that the cryptocurrency market can provide for conventional financial assets.

Predicting Bitcoin returns is challenging, as this digital asset class is characterized by few features such as: high volatility, nonlinear behavior, and frequent changes in market regime (Pedroso et al., 2025). In addition, to the above observation, Zhang et al (2018) argue that Bitcoin returns exhibit statistical properties specific to financial assets (stylized facts), such as volatility clustering, heavy tails, and nonlinear dependencies, which limit the ability of traditional methods based on stable relationships and fixed-parameter indicators to capture the full dynamics of the market.

Moreover, the market regime-dependent nature of Bitcoin returns suggests that the exclusive use of technical rules with constant parameters may be insufficient in all phases of the market cycle. This observation is also one of the motivations for employing the GPR framework. Additionally, the development in this research of the Regime Switch strategy, complements the predictive signal of the GPR model with information on the market regime derived from the MA50/MA200 ratio captured the day before.

Based on these observations, our research investigates whether Bitcoin's overnight returns contain relevant predictive information for the intraday returns of listed companies with direct exposure to the cryptocurrency ecosystem. The relationship is modeled using Gaussian Process Regression, a non-parametric Bayesian model capable of capturing complex functional relationships without imposing a pre-established functional form. We note that the central objective of our research does not consist in comparing Machine Learning (ML) algorithms or in demonstrating the superiority of a particular predictive method, but our central objective is to evaluate how the same predictive information can generate different investment outcomes depending on the decision-making mechanism used in trading stocks in order to build an investment portfolio.

The paper contributes to the literature from four complementary perspectives. First, it extends research on predictive relationships between the Bitcoin market and the stock market by investigating a relationship between Bitcoin's overnight returns and the intraday returns of listed companies with direct exposure to the cryptocurrency ecosystem. Second, we show that the economic value of a prediction model is not determined only by statistical performance, but rather by the correlation between statistical information and the way it is transformed into investment decisions. Third, we highlight the role of market context in interpreting predictive signals and show that implementing decision rules depending on the direction of Bull or Bear can lead to improved risk-adjusted performance. Fourth, the research focuses on individual crypto-exposed companies, while most existing studies analyse the relationships between Bitcoin and stock market indices or aggregate portfolios. Through this latter approach, we also contribute to expanding the empirical evidence on the informational efficiency of these assets.

METHODOLOGY

One of the objectives of the research is to evaluate the predictive and investment performance in an experimental framework that limits the main sources of overestimation of the results encountered in the literature on ML applied to finance. More specifically, we pursue the development of the model and the evaluation of investment strategies through a strict separation between the training, validation and testing periods, thus avoiding the use of future information in the estimation process in the final out - of - sample (OOS) phase. This approach contributes to reducing the risk of look-ahead bias, data leakage and optimism bias, thus providing a more realistic assessment of the generalization capacity of the model and the robustness of the strategies under different market conditions.

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From a methodological point of view, one of the objectives of the research is to evaluate the predictive and investment performance in an experimental framework that limits the main sources of overestimation of the results encountered in the literature on ML applied to finance. More specifically, we pursue the development of the model and the evaluation of investment strategies through a strict separation between the training, validation and testing periods, thus avoiding the use of future information in the estimation process in the final OOS phase. This approach contributes to reducing the risk of look-ahead bias, data leakage and optimism bias, thus providing a more realistic assessment of the generalization capacity of the model and the robustness of the strategies under different market conditions.

Regarding the design of the strategies, the research proposes and compares three investment strategies built on the basis of the same predictions generated by the Gaussian Process Regression model. The first strategy (generically called Original) directly uses all predictive signals generated by the model, the second (Bucket Filtered strategy) introduces an additional mechanism for selecting transactions by filtering them based on historical performance (learned during the validation period), and the third adapts the decision-making rules depending on the Bull or Bear regime of the Bitcoin market. As mentioned, the performance of the strategies is evaluated through a careful procedure of separation between the training, validation and testing periods, in order to limit the risk of overfitting and to analyze the robustness of the results out of

sample. In addition, the results are compared with the passive Buy-and-Hold strategy, both from the perspective of absolute returns and through risk-adjusted indicators.
The literature review highlights two insufficiently explored directions that underpin our approach in this research. First, most studies investigate the relationships between Bitcoin and financial markets at the level of aggregate stock market indices, while research dedicated to individual companies with direct exposure to the cryptocurrency ecosystem remains relatively limited. Moreover, recent literature explicitly highlights this direction as insufficiently developed, mentioning the need to extend empirical evidence to the level of individual stocks (see Bouri et al., 2023). The second direction that we identified as deficient refers to the focus of research on the application of ML methods in finance predominantly on improving predictive performance, using statistical indicators such as RMSE, MAE or prediction accuracy, while evaluating the economic value of these predictions through investment strategies is less frequently addressed. In this context, through our study we aim to contribute to reducing these two gaps by investigating the predictive relationship between Bitcoin's overnight returns and the intraday returns of individual crypto-exposed companies, but also by evaluating how the same predictive information is transformed into investment performance through different decision-making models.

FINDINGS

Our results in this research fit the perspective that the passive B&H strategy outperforms the three active strategies in terms of absolute return. In contrast, although the Regime Shift strategy does not exceed the absolute return of the Buy-and-Hold strategy, it records a higher Sharpe Ratio and, in addition, a significantly lower drawdown, suggesting a more efficient use of risk and a more balanced investment profile.
Although our GPR model demonstrates high predictive capacity, the Original strategy, which directly uses all the signals generated by the model, produces modest results in the out-of-sample period and, although it generates a positive result at the portfolio level, its performance remains inferior to the Bucket and Regime Shift strategies. The lower level of profitability of the Original strategy from OOS period in comparison with validation period confirms that predictive performance and investment performance represent distinct dimensions of the evaluation of a financial model and is consistent with the conclusions supported by Buczynski et al. (2021)

CONCLUSIONS

Our research contributes to the vast literature on the application of ML models in investments by demonstrating that the economic value of a predictive model does not depend exclusively on the statistical accuracy of the predictions, but rather on the speed of the process by which they are transformed into investment decisions. Basically, we show that predictive information generated through the Gaussian Process model can lead to different economic outcomes depending on the decision-making mechanism used and more on its adaptation to the market context. In addition, the research proposes a comprehensive evaluation framework based on the separation of training, validation and testing stages and the avoidance of data leakage and optimism bias situations, then we validate the performance under different market conditions and compare the strategies with the Buy-and-Hold benchmark through risk-adjusted indicators. Overall, the results suggest that the robustness and investment efficiency of ML-based strategies are determined by the coherent correlation of three components: (i) the predictive one, (ii) the decision-making mechanism and (iii) the market context.
Although the results obtained and the literature support the robustness of the proposed framework, they must be interpreted in the context of the research limitations, determined by several aspects such as: (i) the investment universe analyzed, (ii) the method used to identify market regimes, (iii) the use of a single predictive model and (iv) the portfolio allocation model. In this context, future research can extend the proposed approach by applying it to other asset classes and economic sectors, integrating more advanced methods for identifying market regimes and evaluating decision-making mechanisms developed in combination with other modern g models degree to which the decision-making mechanisms proposed in this paper retain their efficiency when applied to predictive models other than Gaussian Process Regression. Regarding, the fourth limitation we used here an equally-weighted portfolio with a fixed allocation of $100,000 divided equally across symbols. However, we acknowledge that this is only a

baseline scenario. We did not explore other capital allocation methods – such as risk-optimized or volatility-based allocations. Thus, an additional future direction of research could investigate how the performance of our strategies changes in the context of different allocations. The results of our research have implications for both academia and investment practice. From an academic perspective, the study contributes to the understanding of how information from the Bitcoin market can be capitalized in anticipating the price direction of individual stocks with exposure to the cryptocurrency ecosystem, extending the literature that has predominantly focused on stock indices or aggregate portfolios. At the same time, the results reiterate that the evaluation of Machine Learning models should not be limited only to the statistical performance of the predictions, but should also include the analysis of the mechanisms (applied filters) through which predictions can be transformed into investment decisions in dynamic market contexts. From a practical perspective, the research suggests that the integration of information regarding the market regime and the use of adaptive decision-making rules can lead to improved risk-adjusted performance, providing investors with a systematic framework for capitalizing on the predictive information generated by Machine Learning models.

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