199 Report

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1 Introduction

In this analysis, we explore the extent to which well-known market effects from traditional financial markets, such as seasonality, momentum, mean-reversion, carry, etc. are present in the cryptocurrency markets. These phenomena have been well-documented in the more traditional financial markets, such as equities and fixed income, where they are leveraged in various trading strategies. However, the unique idiosyncrasies of crypto markets that separate them from traditional markets - such as their relatively young infrastructure, decentralization, volatility, the risk-appetite of customers - suggest that these effects may be exacerbated, behave differently, or perhaps fail to manifest altogether.

Specifically, in this analysis, we investigate seasonality effects in cryptocurrency markets, focusing on patterns based on the day of the week and patterns based on the day of the month. Additionally, we examine the presence of trend effects and their potential role in price movements. Moreover, on top of conducting these investigations across an aggregate of cryptocurrencies, we also repeated each of these investigations specifically with Bitcoin. To conduct this analysis, we collected daily price data from the past 5 years from the top 50 cryptocurrencies ranked by market capitalization using CoinGecko's API. CoinGecko is a provider of cryptocurrency data that offers detailed information across a wide range of coins in the cryptocurrency industry. The goal is to assess whether these phenomena hold relevance in the crypto space, and with these phenomena in mind, to identify unique patterns that could inform quantitative trading strategies in this asset class.

2 Data Overview, Collection, Pre-Processing

The data consists of a single dataset. This dataset contains the daily prices, beginning on the 1st of January, 2020 to the 1st January, 2025, from the top 50 cryptocurrencies ranked by market capitalization on the date of collection.

2.1 Data Collection

The data for this analysis was collected via the CoinGecko API, which provides comprehensive, granular data on the cryptocurrency market. Initially, a request was made to retrieve the list of the top cryptocurrencies ranked by market capitalization. To ensure the relevance of the dataset and reduce redundancy, stablecoins - cryptocurrencies designed to maintain a stable value, and wrapped tokens - representations of other cryptocurrencies for trading at different venues - were filtered out. Following this, separate requests were made for each of the top 50 coins to obtain their daily closing prices over the past five years, alongside it's timestamp. The resulting time-series data for each asset was then merged using an outer join on the timestamp, to construct a single, comprehensive dataset suitable for analysis.

2.2 Data Pre-Processing

To facilitate the analysis of market effects, the daily closing price data for each cryptocurrency is transformed into daily log returns. Logarithmic returns, defined as $log(\frac{P_t}{P_{t-1}})$, are calculated for each timestamp, where P_t represents the closing price of the asset at time t. This transformation is commonly used in analysis of financial markets because it produces returns that are time-additive, making it easier to model and plot. By using log returns, the analysis accounts for the effects of compounding, enabling a robust assessment of market dynamics.

From the single, comprehensive dataset, we then construct a dataset comprising of the log returns of the top 50 cryptocurrencies in aggregate, where for each day, we take the average of the individuals log returns of each cryptocurrency and average them to a single value. This effectively serves as the dataset of the log returns of an equal-weighted average of the top 50 coins, providing a broader measure of market performance.

Additionally, we create a separate dataset of Bitcoin's returns alone, isolating its returns from to evaluate it independently from the broader market. These smaller sets of data serve as the foundation for the subsequent seasonality and trend analysis.

3 Seasonality Analysis (Day of the Week)

3.1 Aggregate (Equal-Weighted Top 50 Index)

3.1.1 Visual Analysis

To assess whether cryptocurrency demonstrate systemic patterns across the days of the week, we analyze the aggregate time series by grouping daily log returns according to the day of the week. Initially, we compute the average log return for each day of the week and plot them alongside each other. Figure 1 reveals a pronounced weekend effect, where there are strongly positive average returns on Saturday and Sunday, while the rest of the week appears noisy, with no clear pattern.

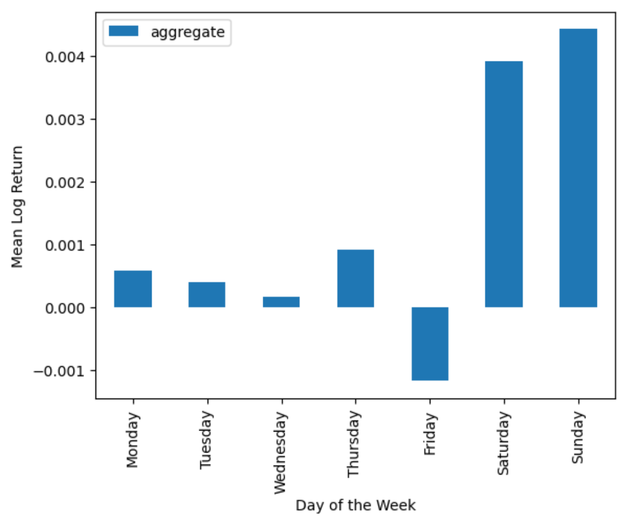

Figure 1: Mean Return of The Aggregate According to the Day of the Week

To mitigate the influence of outliers, we complement this analysis by doing the same with the median log return of each day of the week. The median, here, can serve as a robust measure as it reduces the impact of very extreme values that could distort the general pattern. Figure 2 confirms the weekend effect, showing

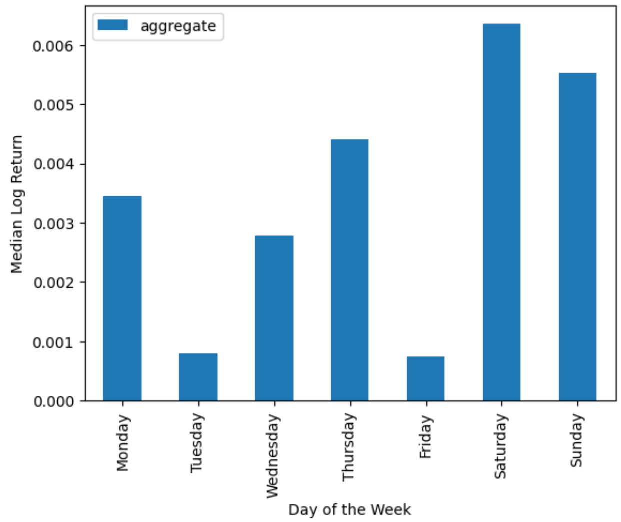

Figure 2: Median Return of The Aggregate According to the Day of the Week

that while all days of the week exhibit modestly positive returns, the weekend stands out with higher returns relative to the rest of the week, although not by a pronounced margin.

Given these simple visual tests, we fail to reject the idea that the returns according to the day of the week are purely random. Therefore, we continue on and construct a simple metric to quantify the weekend effect in a more explicit manner. The metric goes as such: for each week, we compute the difference between the sum of the returns of the weekend and the sum of the returns of the rest of the week. We then visualize this metric as a bar plot in Figure 3. There appear to be slightly more weeks where the metric is positive than it is negative, with the magnitudes distributed nearly symmetrically, but overall the results seem inconclusive.

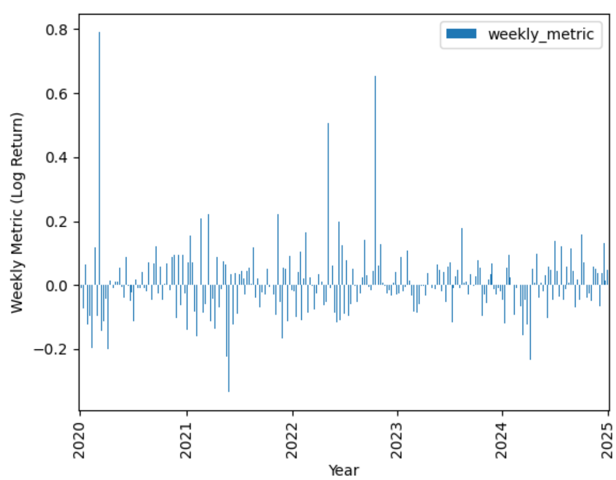

Figure 3: Bar Chart of the Weekly Metric of The Aggregate

To further evaluate this effect, we compute and plot the cumulative sum of this weekly metric over time, effectively simulating the performance of a strategy that seeks to exploit the weekend anomaly. Figure 4 suggests that an account following the strategy from 2020 to 2025 would have approximately doubled in value in log return terms, translating to a 539% increase in normal return terms; however, the path is highly volatile and noisy.

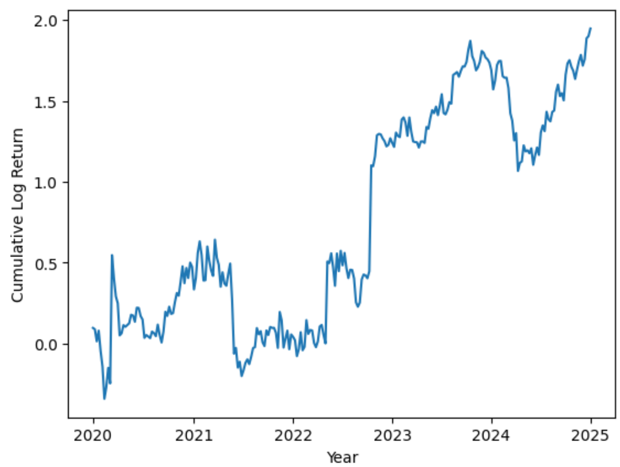

Figure 4: Cumulative Log Returns of a Simulated Day of the Week Seasonality Strategy on an Equal-Weighted Index of the Top 50 Coins ex. Transaction Costs, Slippage, etc.

3.1.2 Statistical Testing

Since our visual tests didn't outright reject the presence of the weekend effect, we proceed to formal statistical tests. To formally test whether the observed weekend effect is statistically significant, we conducted two non-parametric hypothesis tests: the Kruskal-Willis Test and a permutation test.

The Kruskal-Willis test, a generalization of ANOVA, assesses whether samples originate from the same distribution without assuming normality. This test is particularly useful, since cryptocurrency returns may exhibit heavy tails. The Kruskal Willis test returns a p-value of 0.26, which at a significance level of 0.05 leads us to fail to reject the null, suggesting no strong evidence against purely random returns.

We then perform a permutation test, shuffling the day of the week associated with the returns to produce a null distribution for the test statistics, defined as the difference in mean returns between the weekend and the rest of the week. Doing so allows us to investigate whether the observed weekend premium is likely to have been due to chance. The permutation test yields a p-value of 0.08, which, while lower than that of the Kruskal-Willis test, remains above the conventional significance level of 0.05, leading us to fail to reject the null hypothesis.

While the weekend effects appears to be visually suggestive, our statistical tests do not provide sufficient evidence to conclude that it is a persistent, exploitable effect, and if it is, it is an effect subject to significant variability in outcome, and may take many years to realize it's expected returns.

3.2 Bitcoin

3.2.1 Visual Analysis

As in the previous analysis done with the aggregate, we examine the effect by grouping the returns of Bitcoin by the day of the week, and computing both the mean and median for each day. As Figure 5 and Figure 6 show, unlike the broader market's weekend effect, Bitcoin exhibits a different pattern: Mondays and Fridays show significantly lower returns relative to the rest of the week, where Fridays are strongly negative.

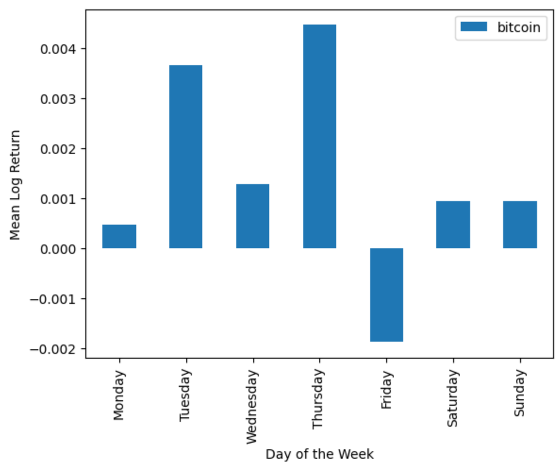

Figure 5: Mean Return of Bitcoin According to the Day of the Week

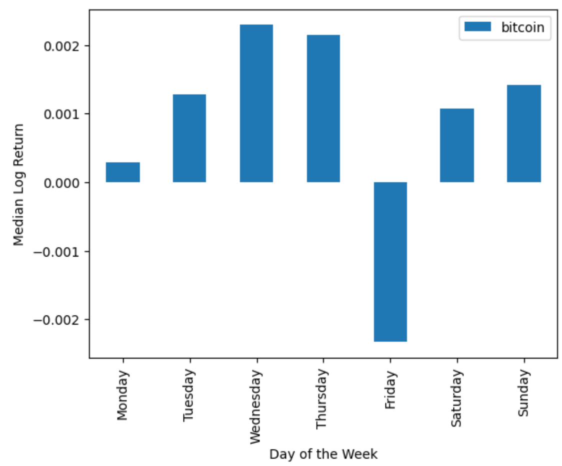

Figure 6: Median Return of Bitcoin According to the Day of the Week

Given this observed idiosyncrasy, we construct a simple metric that captures the difference in the sum of the returns of the proposed stronger days and the sum of the returns of the weaker days. Much like in the previous analysis, the metric is slightly frequently positive than negative, and the magnitudes are about the same, but mostly inconclusive, as Figure 7 demonstrates. When plotted cumulatively, Figure 8 shows that metric suggests that an account following the strategy would have tripled in log return terms from 2020 to 2025, equating to a 1,908% return, although with some variability.

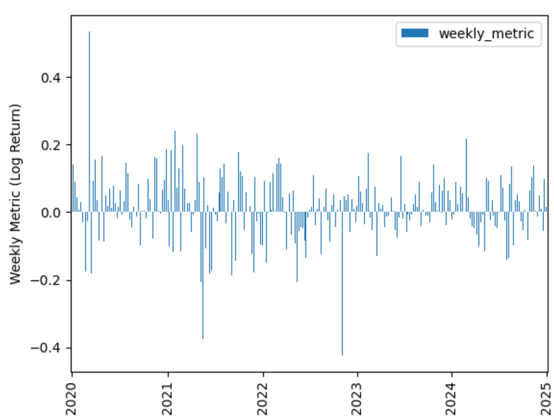

Figure 7: Bar Chart of the Weekly Metric of Bitcoin

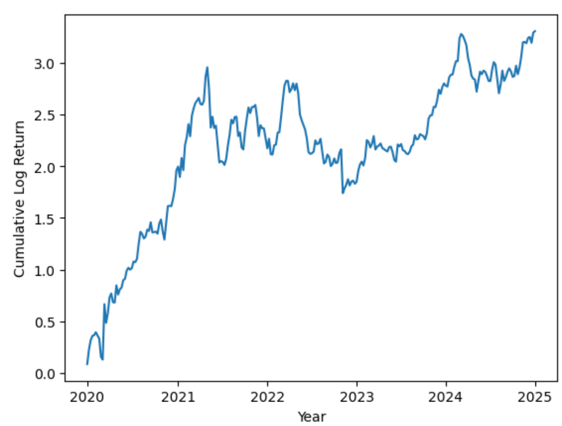

Figure 8: Cumulative Log Returns of a Simulated Day of the Week Seasonality Strategy on Bitcoin ex. Transaction Costs, Slippage, etc.

3.2.2 Statistical Testing

Performing the same tests as in the previous analysis, the Kruskal-Willis test produces a p-value of 0.62, and the permutation test returns a p-value of 0.09 - both failing to reject the null hypothesis at the significance level of 0.05. While it seems that behavior of the price movements of Bitcoin on a day of the week basis may be different than that of the broader market, our findings do not provide strong enough evidence to reject the proposition that it may simply be due to noise.

4 Seasonality Analysis (Day of the Month)

4.1 Aggregate (Equal-Weighted Top 50 Index)

4.1.1 Visual Analysis

To examine potential seasonality effects based on parts of the month, we begin by grouping daily log returns according to their calendar day and computing the mean return for each day. As Figure 9 indicates, returns in the first and last week of the month were consistently positive, while the rest of the month exhibits considerable noise. We also compute the median returns grouped by day of the month as well, and as Figure 10 reveals, interestingly, the median returns are mostly positive across the board. While it shows no clear pattern, it demonstrates an interesting characteristic of the daily returns, which is that they are skewed with a heavy left tail.

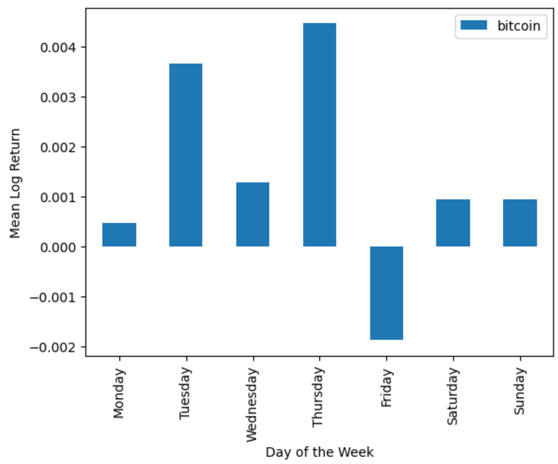

Figure 9: Mean Return of The Aggregate According to the Day of the Month

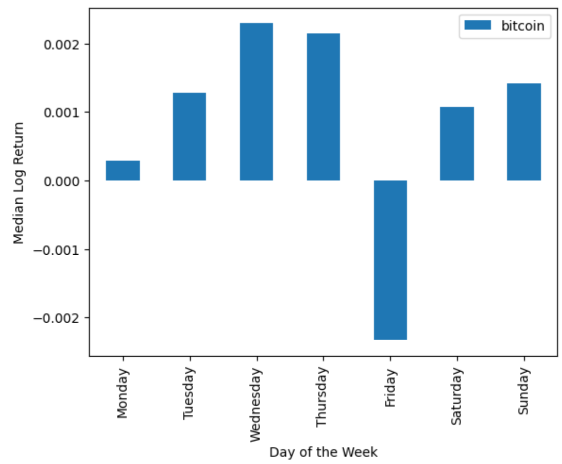

Figure 10: Median Return of The Aggregate According to the Day of the Month

To further investigate, we repeat the computation of the mean return according to the day of the month, for each year of the past five years. This breakdown, demonstrated in Figure 11, reveals a persistent effect: returns in the final five days of the month are consistently positive across all years, suggesting a month-end anomaly.

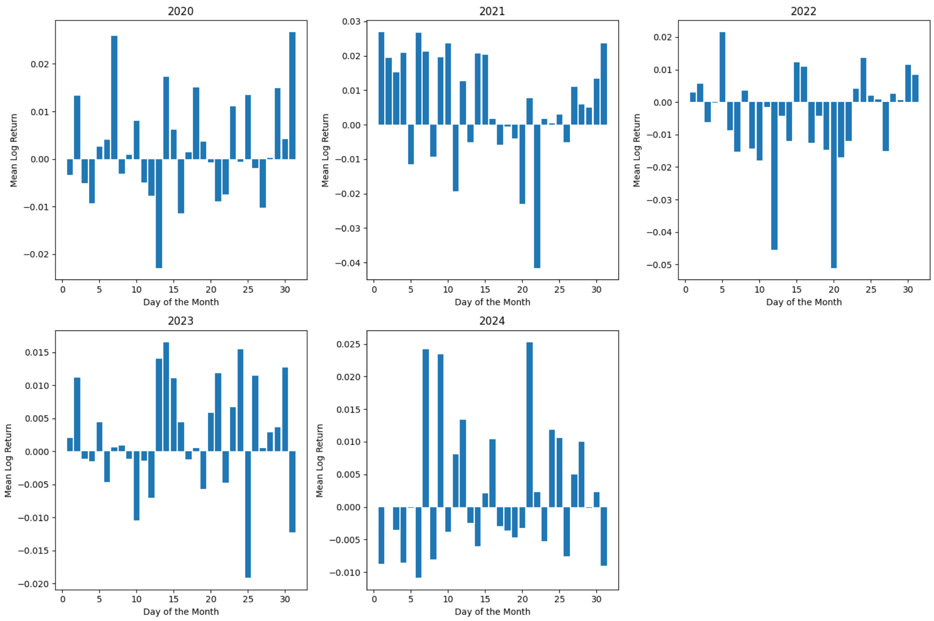

Figure 11: Breakdown by Year of the Mean Returns of The Aggregate According to the Day of the Month

To quantify this effect, we define a simple monthly metric, computed as the sum of the log returns over the last five days of each month, and plot it as a bar plot. Figure 12 shows this metric is slightly more frequently positive than negative, and the magnitudes are roughly balanced. As Figure 13 indicates, a cumulative plot of this metric over time suggests that a strategy exclusively exploiting this pattern would have a cumulative log return of 0.9, translating to 146% return in regular return terms (excluding transaction costs, slippage, etc.).

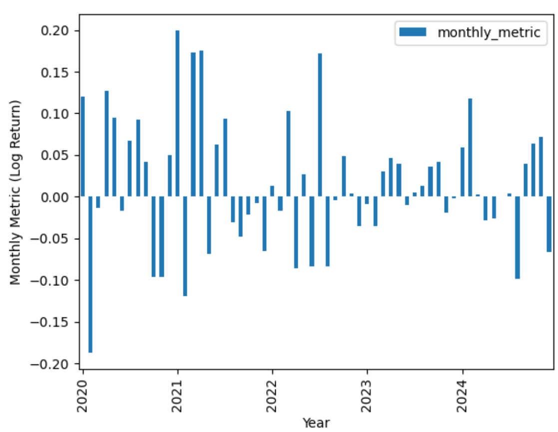

Figure 12: Bar Chart of the Monthly Metric of The Aggregate

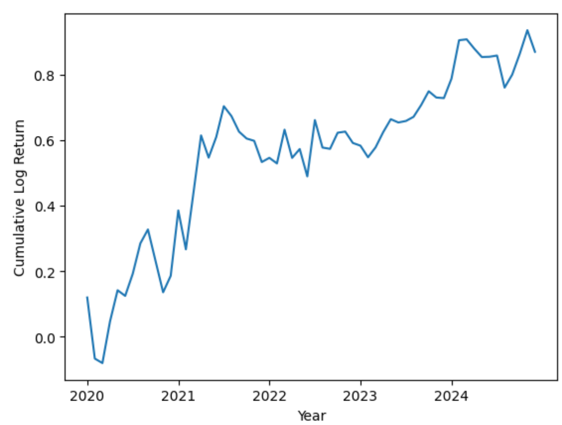

Figure 13: Cumulative Log Return of a Simulated Day of the Month Seasonality Strategy on an Equal-Weighted Index of the Top 50 Coins ex. Transaction Costs, Slippage, etc.

4.1.2 Statistical Testing

Moving beyond our visual analysis, which suggests an end-of-month effect, we move to statistical tests to formally assess the presence of this effect.

A Kruskal-Willis test, which evaluates whether returns vary systematically across different days of the month, produces a p-value of 0.31, suggesting no statistically significant differences. In addition, a permutation test, where we permute the day of the month corresponding to each return observation for each month, and compare against the observed test statistic of the difference in mean returns between the final days of the month and the rest of the month. This test yields a p-value of 0.43, failing to reject the null hypothesis, the assumption that returns on different days of the month are drawn from the same distribution, and that any observed patterns are likely due to chance.

Although visually suggestive, there is not strong enough evidence to reject the assumption that this perceived pattern has arisen purely due to chance. Or, if the effect were to exist, it could simply be too weak and too noisy to detect given our sample size.

4.2 Bitcoin

4.2.1 Visual Analysis

As in our previous analysis of seasonality based on the day of the month with the equal-weighted aggregate, we conduct an analysis focusing solely on Bitcoin. We begin by grouping the log returns by the month and computing the mean. As Figure 14 indicates, the returns at the end of the monthly are strongly positive, with the rest of the month exhibiting significant noise. As for the median, Figure 15 demonstrates results that align very closely with that of the mean grouped by day of the month.

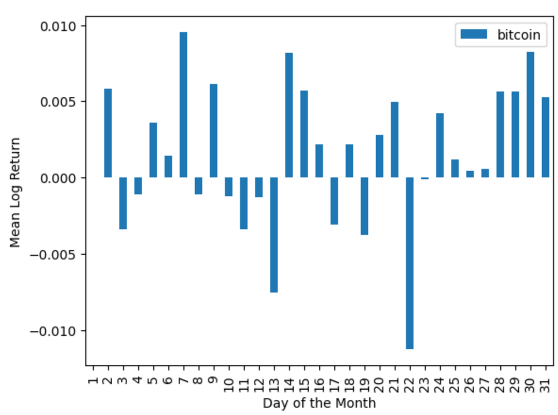

Figure 14: Mean Return of Bitcoin According to the Day of the Month

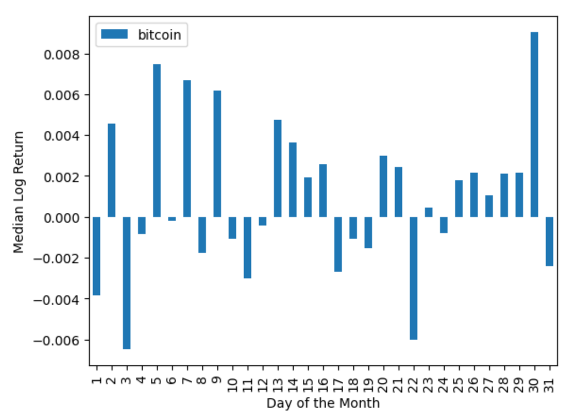

Figure 15: Median Return of Bitcoin According to the Day of the Month

To determine it's persistence more granularly, we repeat the computation of the mean return for each day of the month for each year of the past five years. As Figure 16 indicates, across all years, the last five days of the month exhibit consistently positive returns in each year, with the rest of the month showing no clear pattern.

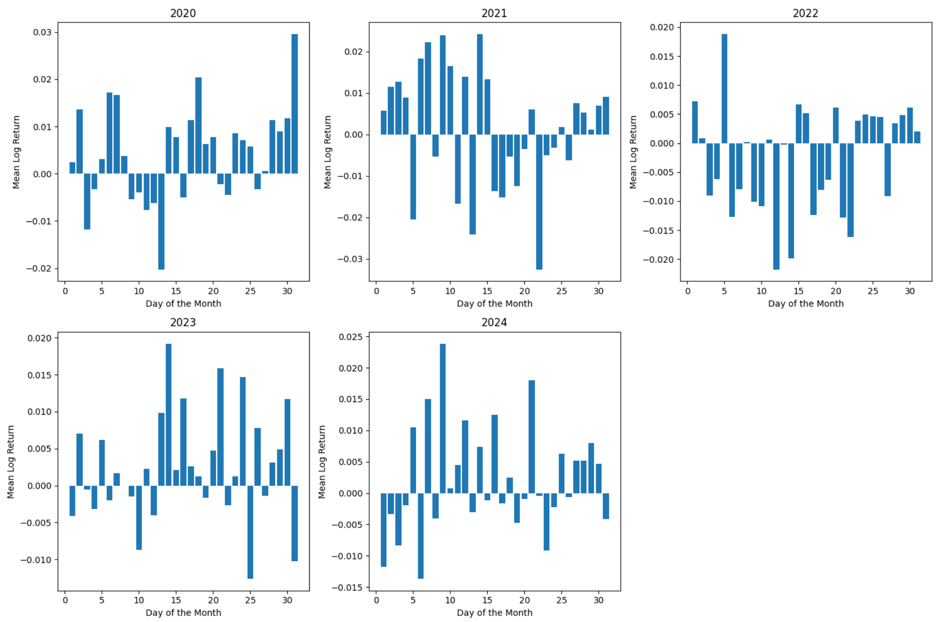

Figure 16: Breakdown by Year of the Mean Returns of Bitcoin According to the Day of the Month

Further analyzing this effect, we compute the metric utilized in the previous analysis, and plot it. According to Figure 17, the metric appears to be more frequently positive than negative, with similar magnitudes in both directions. A cumulative plot of this metric shows that a strategy based on exploiting this end-of-month effect would have achieved a cumulative log return of 1, or a 172% return over the period studied, as indicated in Figure 18.

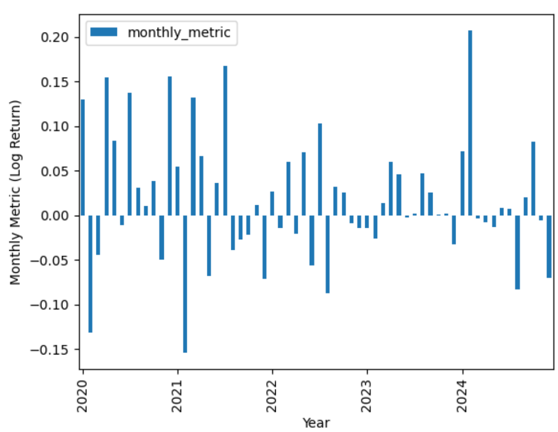

Figure 17: Bar Chart of the Monthly Metric of Bitcoin

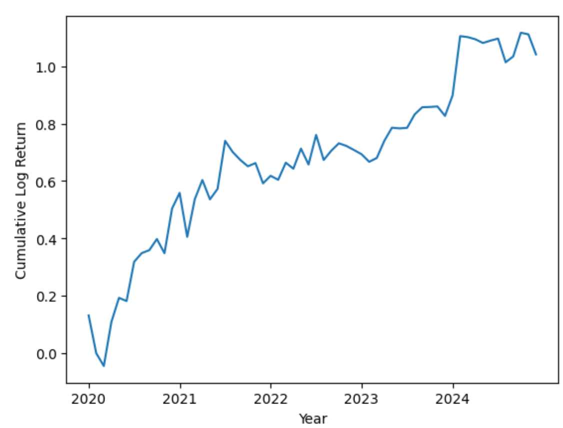

Figure 18: Cumulative Log Return of a Simulated Day of the Month Seasonality Strategy on Bitcoin ex. Transaction Costs, Slippage, etc.

4.2.2 Statistical Testing

Testing the statistical validity of this anomaly, a Kruskal-Willis test yields a p-value of 0.15, while a permutation test - structured the same way as in the previous analysis - yields a p-value of 0.23. As in the aggregate case, these results cause us to fail to reject the null hypothesis of non-seasonality.

5 Trend (Time-Series Momentum) Analysis

5.1 Aggregate (Equal - Weighted Top 50 Index)

5.1.1 Visual Analysis

To assess whether trend effects are present in the aggregate, we examine the cumulative log return over the past five years. Figure 19 suggests periods of trending behavior, but further analysis is required.

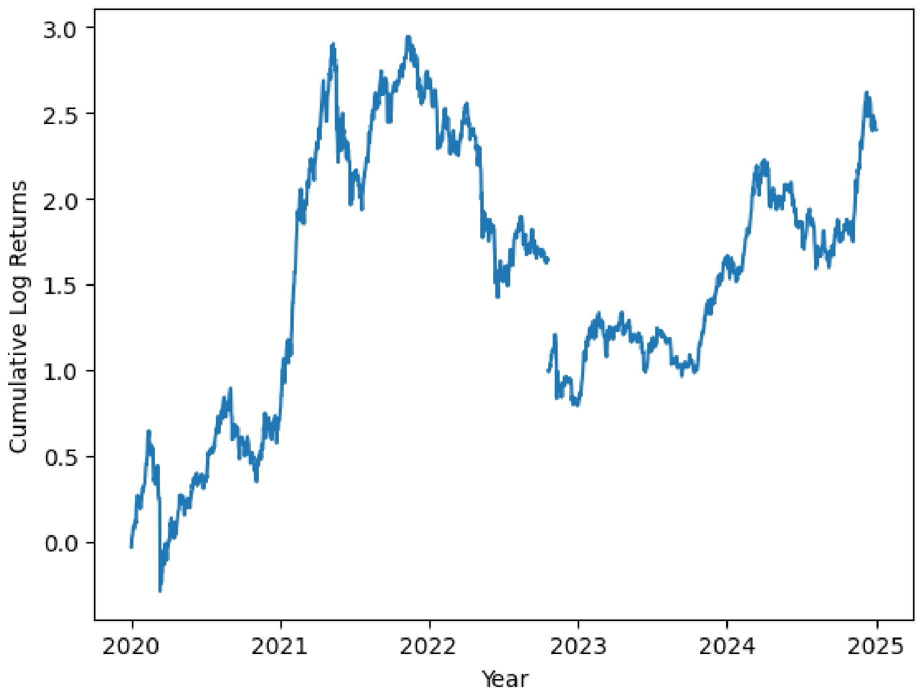

Figure 19: Cumulative Log Returns of an Equal-Weighted Index of the Top 50 Coins from 2020 to 2025

We then analyze the relationship between past and future returns by computing the average log return for each period in the dataset, where a period is defined as a series of days, and plotting it against the average return of the following period, along with a fitted regression line. Doing this for different period lengths (e.g. 1 day, 3 days, 5 days, etc.). If returns exhibit trending behavior, we would expect a positive slope. As Figure 20 indicates, there is a slightly negative slope for a 1-day period, a slightly positive slope for a 3-day period, and beginning with a 5-day period the slope increases up to when the period length reaches 20 days, before declining once again. This pattern visually suggests that returns may exhibit trending behavior over intermediate time horizons, though the effect weakens at longer horizons.

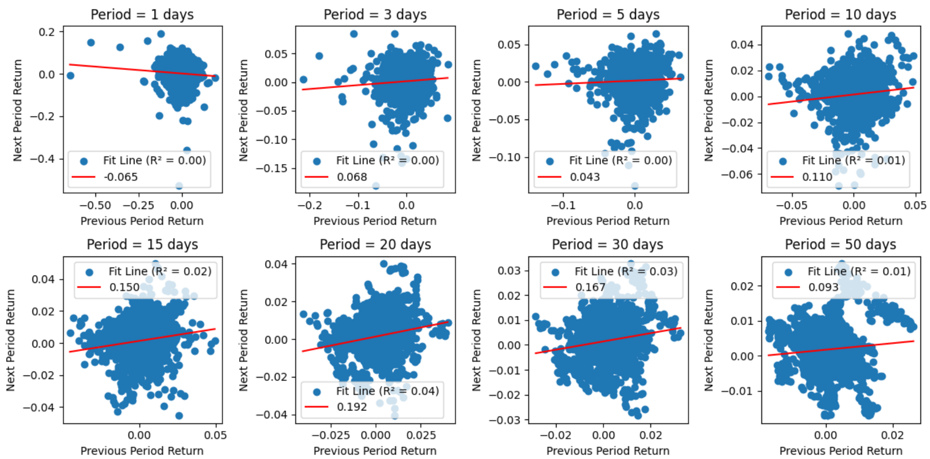

Figure 20: Plot of Previous Period's Mean Log Return against Next Period's Mean Log Return for Periods of lengths: 1 day, 3 days, 5 days, etc.

To further investigate, we compute the autocorrelation function (ACF) of log returns up to a lag of 30 days. Figure 21 shows that the ACF immediately drops close to zero after the first lag, indicating little persistence in returns. However, this result on it's own is not conclusive, as the ACF measures correlations at individual lags, but does not account for dependencies that may emerge jointly across multiple periods.

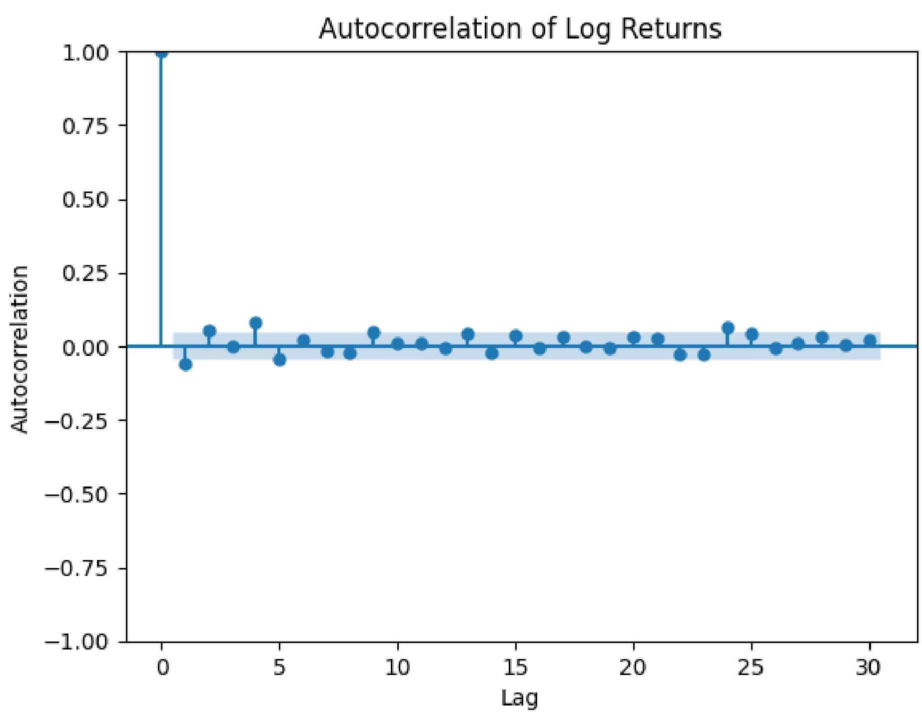

Figure 21: ACF (Autocorrelation Function) of The Aggregate

5.1.2 Statistical Testing

To statistically test for the presence of a trend effect, we conduct the Ljung-Box test on the log returns up to a lag of 30 days. This test examines whether the autocorrelations of a time series are jointly equal to zero.

The results for this test yield p-values below starting at 0.007 and decreasing to a minimum of 0.000169 at a lag of 25, before rising again. This suggests some degree of autocorrelation up to larger lags.

We also fit an AR (AutoRegressive) model with up to 30 lags. An AR model models how past returns can predict future returns by expressing the return at time t, r_t, as a linear combination of previous return values r_{t-1}, r_{t-2} etc. The p-values of the estimated coefficients of this model vary widely, ranging from 0.01 to 0.98 with no discernible pattern - some lags exhibit statistical significance, while others do not, with no apparent relationship with respect to lag length. This lack of structure does not provide sufficient evidence to indicate the presence of a trend effect.

While the analysis hints at the presence of trending behavior, the statistical evidence is not sufficient enough to support it. If trends exist in the broader market, they are weak, and dominated by noise.

5.2 Bitcoin

5.2.1 Visual Analysis

To examine whether Bitcoin exhibits trend effects, we conduct an analysis identical to that applied to the aggregate index. Plotting the cumulative log returns of Bitcoin over the past five years, visual inspection suggests the presence of trends, as Figure 22 indicates.

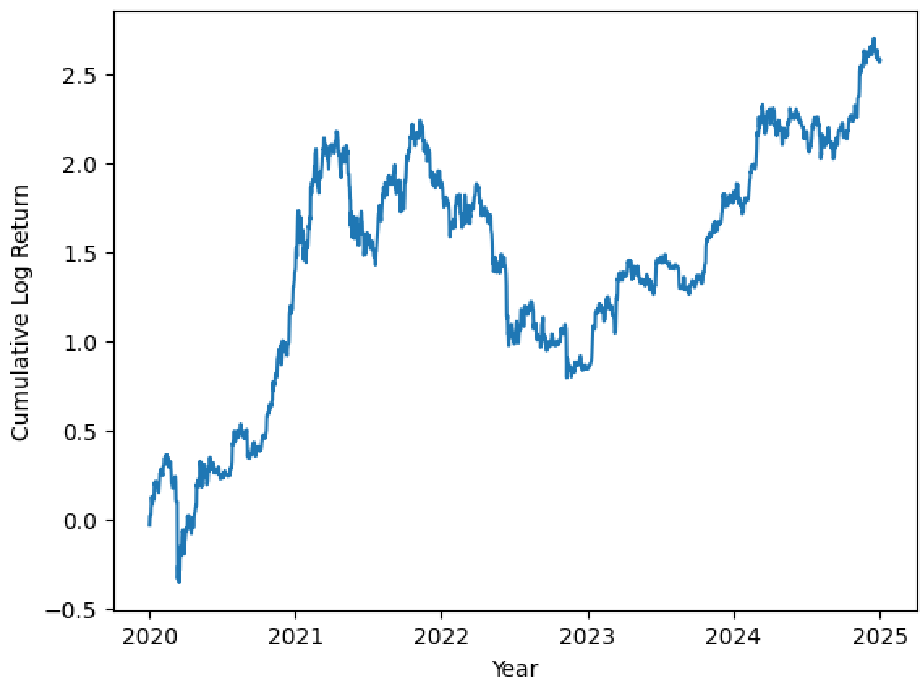

Figure 22: Cumulative Log Returns of Bitcoin from 2020 to 2025

Plotting the average log return for each period against the average log return of the next period and fitting a regression line, for periods up to 50 days, we see results similar to that of the aggregate. Figure 23 shows that a 1-day period the slope is slightly negative, but as period lengths are increased, the slope increases just as well, peaking at a period length of 30 days, before declining again. This pattern suggests that returns exhibit trending behavior over intermediate timeframes, but weakens at much shorter or much longer timeframes, much like the aggregate.

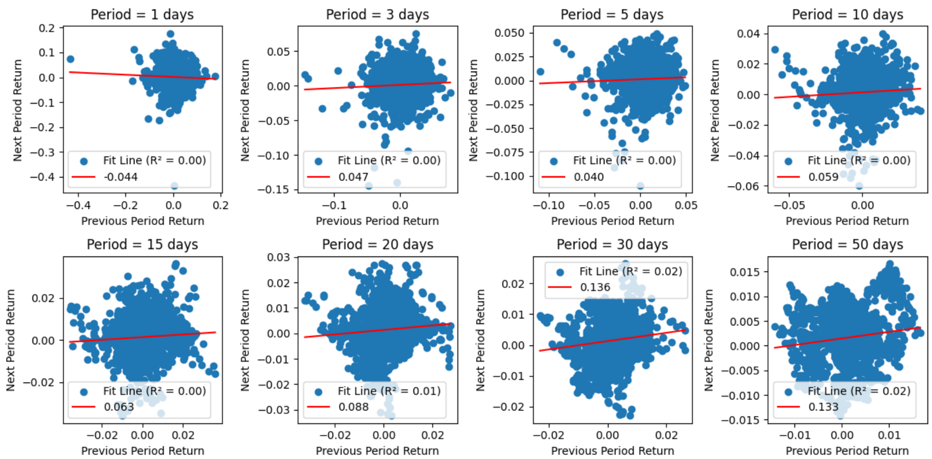

Figure 23: Plot of Previous Period's Mean Log Return against Next Period's Mean Log Return for Periods of lengths: 1 day, 3 days, 5 days, etc.

Examining further, we compute and plot the ACF (Figure 24). Similar to the aggregate, the autocorrelation drops to zero immediately after the first lag, suggesting little to no persistence in daily returns on the time scale we are investigating.

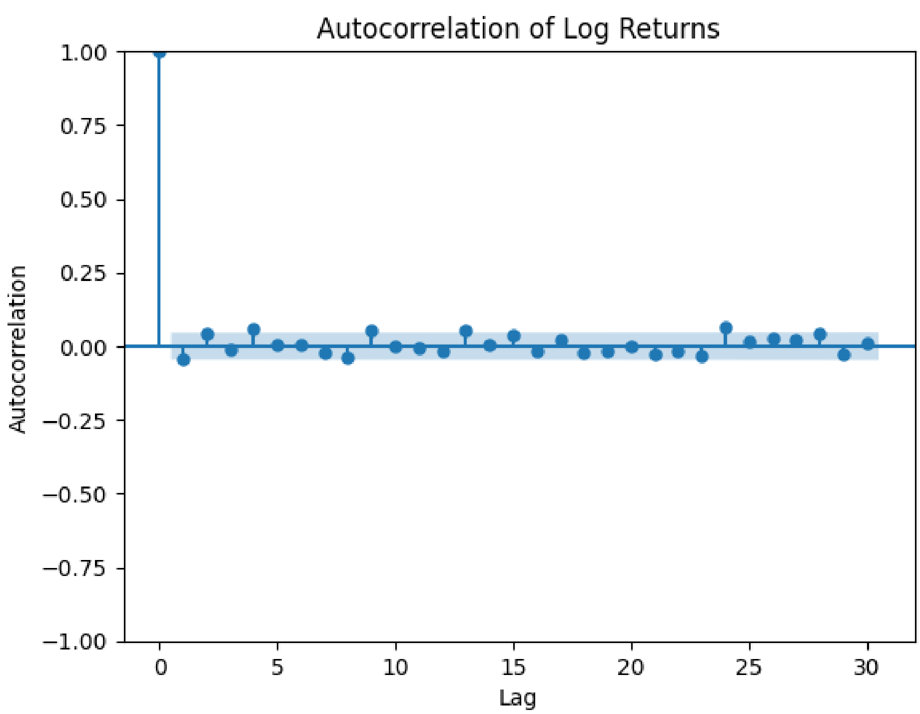

Figure 24: ACF (Autocorrelation Function) of Bitcoin

5.2.2 Statistical Testing

For a statistical test of trending behavior, we conduct a Ljung-Box test up to 50 lags. The results show a p-value of 0.058 at lag 1, 0.029 at lag 2, and 0.064 at lag 3. Beyond this, the p-values remain below the conventional significance level of 0.05, declining until lag 47, where they begin to increase noticably again.

We further examine the presence of trend effects by fitting an AR model to Bitcoin's log returns. The resulting p-values range from as low as 0.013 to as high as 0.936, without any discernible pattern - some lags may be statistically significant, but overall the significance does not systematically increase or decrease with lag length. This erratic distribution of p-values, indicate that any dependencies are inconsistent, and the returns do not follow a clear trend-based structure.

While certain analyses may suggest the possibility of trending behavior over intermediate timeframes, the statistical evidence remains weak. These results align with those observed for the aggregate index, where if trend effects exist, they may not be strong enough to be exploited.

6 Discussion and Suggestions

Given the characteristics of cryptocurrency markets - such as their relative nascence, lower regulatory oversight, and high retail participation - one might expect these markets exhibit inefficiencies similar to those well-known in traditional financial markets, and potentially in a more pronounced manner. However, our analysis suggests that this may not be the case, at least for the market anomalies we specifically investigated.

We examined seasonality effects based on both the day of the week as well as the day of the month, resulting in not sufficiently strong evidence to reject that any pattern may have been due to chance. Similarly, when investigating the presence of trend effects, we found mixed results. While visual inspection suggested some degree of trending behavior, statistical tests produced inconclusive results.

It is important, however, for us to acknowledge the limitations of our study. First, we have a relatively small sample size of five years worth of daily price data. This data may reflect recent market dynamics, but it does not allow us to investigate inefficiencies on a much longer-term basis throughout cryptocurrency history. In addition, we focused our investigation on a specific set of well-documented market effects. There are numerous other inefficiencies that we did not explore, such as momentum effects at different time scales, cross-sectional effects such as size and low-volatility, or even inefficiencies unique to crypto - such as the structural inefficiencies related to funding rates and perpetual swap dynamics.

Future research could extend this analysis in multiple ways. Expanding the dataset length to incorporate a more extensive history could provide a much stronger analysis of the inefficiencies we investigated, with a much larger sample size. Incorporating intra-day data might also reveal short-term inefficiencies that were masked on a daily timescale. In addition, expanding the scope of analysis to alternative inefficiencies - such as those related to cross-sectional factors, exchange-specific price deviations, or the impact of large liquidations, etc. - could provide a more comprehensive assessment of inefficiencies in the cryptocurrency markets and their similarities or lack thereof with the inefficiencies that exist in traditional financial markets.

7 Conclusion

Overall, while our findings suggest that certain well-known market inefficiencies may not be present in cryptocurrency markets as one might expect, this does not imply that inefficiencies are absent altogether. Rather, it suggests for further research to identify and understand the unique dynamics at play in these markets.