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Calendar Effects on Returns, Volatility and Higher Moments: Evidence from Crypto Markets

Bernardina Algieri^{*†} Kokulo Lawuobahsumo^{*} Arturo Leccadito^{*‡}
Iliess Zahid^{*}

Abstract

This study aims to investigate calendar effects in the cryptocurrency market. We consider the day-of-the-week, the month-of-the-year, quarter-of-the-year, the US Holidays, and Weekend calendar anomalies for the leading cryptocurrencies: Bitcoin, Dash, Dogecoin, Litecoin, Ripple, and Stellar. Our study employs the Autoregressive Conditional Density model with dummy variables to scrutinize these calendar effects. We find anomalies in the mean, variance, skewness, and kurtosis for these cryptocurrencies' returns. Our result suggests that the cryptocurrency market in some periods tends to violate the Efficient Market Hypothesis.

Keywords: Calendar effects, Higher Moments, Cryptocurrencies

JEL: C58, E44, G15

^{*}University of Calabria, Department of Economics, Statistics and Finance, Ponte Bucci, Rende (CS), 87036, Italy

[†]Department of Economic and Technological Change, Zentrum für Entwicklungsforschung (ZEF), Universität Bonn, Walter-Flex-Straße 3, Bonn, 53113, Germany

[‡]LFIN/LIDAM, UCLouvain, Voie du Roman Pays 34, Louvain la Neuve, 1348, Belgium

1 Introduction

Technological development and digital change are upending the financial system. Over the last few years, cryptocurrencies have become very popular for their unique properties that differentiate them from traditional financial assets such as commodities, stocks, and bonds. Cryptocurrencies exhibit complex risk dynamics such as high volatility, pronounced asymmetries, and high tail risk, with extreme fluctuations in the returns. The characteristics of these assets make it challenging to model their risk and manage portfolios containing these assets.

Bitcoin, the main cryptocurrency, can be seen as a Decentralized Autonomous Organization (DAO), an open-source, peer-to-peer digital network that imposes its founding rules. The integrity of the network eliminates the need for human participants because, in a DAO setting, rules based on an algorithm define the cryptocurrency supply.

Since Nakamoto (2009) introduced and documented Bitcoin as an electronic payment system based on cryptographic proof, the dynamics of cryptocurrencies have attracted attention from a broad perspective, including market participants and academicians (Vasek, 2015; Geuder et al., 2019). As suggested by Fry and Cheah (2016), Bitcoin properties have drawn divergent opinions economically. For instance, Baeck and Elbeck (2015) classify Bitcoin as a speculative asset, not a genuine currency. In contrast, Selgin (2015) claims that Bitcoin has functioned as a monetary instrument that investors have utilized for both investment and demonetization purposes.

Even though cryptocurrencies are high-risk assets, they are becoming attractive to an increasing number of new retail and institutional investors, with cryptocurrency ETNs and derivatives, including futures and options, now traded in the market. With the growing interest in these digital assets, studies such as Lawuobahsumo et al. (2023); Basher and Sadorsky (2022); Bakas et al. (2022); Wang et al. (2022); Borri (2019) have focused on the determinants of cryptocurrency returns. Due to the high volatility behavior of cryptocurrencies, Lawuobahsumo et al. (2023) show that the VIX index,

the Treasury Yield Spread, the 5-year Forward Inflation Expectation Rate, and the 10-year Breakeven Inflation Rate are significant determinants of cryptocurrency tail risks. Basher and Sadorsky (2022) report that technical indicators, such as MA50, WAD, MACDSignal, and macroeconomic variables, like the oil volatility index and ten-year bond yields, can predict Bitcoin price direction. Wang et al. (2022) show that technical indicators are more accurate in forecasting Bitcoin volatility during low volatility phases. Bakas et al. (2022) show that Google trends can positively impact Bitcoin volatility, while total circulation of Bitcoins, the US consumer confidence, and the S&P500 index have a negative effect on Bitcoin volatility. Conversely, Borri (2019) finds no exposure of cryptocurrency tail risks arising from assets such as equities or gold. Cryptocurrencies not only lack any intrinsic value but also do not pay dividends. Furthermore, they are not accepted as legal tender or an official medium of exchange. With Bitcoin having a limited supply, investors can believe that buying it will enable them to sell it at a higher price later, which can result in speculative bubbles. Bitcoin has seen its price rise to around \$20,000 per coin between August and December 2017 and a similar fall between May and June 2021. These patterns may be due to the “fear of missing out” of many private investors.

Starting from this background, the present study aims to explore calendar effects in the cryptocurrency market. Calendar effects are anomalies in financial returns related to the calendar, such as the day-of-the-week, the month-of-the-year, the quarter-of-the-year, or holidays. Equities, for instance, would trade the least amount on Mondays and register high returns on Fridays (e.g. Birru, 2018; Kiymaz and Berument, 2003). Bouman and Jacobsen (2002) show that stock returns are lower in the summer months (from May to October) and higher in the winter months (from November to April); this is the so-called “sell-in-May-and-go-away” effect and the Halloween effect (leaving the market in May and coming back after Halloween, 31 October). The presence of calendar effects gives rise to predictable patterns in returns exploitable by market participants.

Calendar effects imply, indeed, that at a particular period, financial returns behave contrary to the Efficient Market Hypothesis¹ (EMH) proposed by Fama (1965), and the existence of a systematic pattern creates an opportunity to earn abnormal returns through the existing information. Thus, taking advantage of calendar effects or seasonal anomalies may be beneficial in terms of investment timing.

From this backdrop, we endeavor to study the calendar anomalies of six cryptocurrencies, namely Bitcoin, Dash, Dogecoin, Litecoin, Ripple, and Stellar. Similar to Kinatader and Papavassiliou (2021), we explore several calendar anomalies, such as the day-of-the-week (DOW), the month-of-the-year (MOY) Quarter-of-the-Year (QOY), the US Holidays and Weekend calendar effects, for the selected cryptocurrencies. Contrary to Kinatader and Papavassiliou (2021), we employ the Autoregressive Conditional Density (ACD) model with dummy variables and hence broaden the investigation of these calendar anomalies to include higher moments, namely skewness and kurtosis, in addition to mean and variance. The ACD model is an extension of the GARCH model, allowing for time variation in higher moments, thus providing a deeper understanding of the sources of seasonalities at different moment levels.

Studying anomalies in higher moments is relevant since they give insights into the shape and behavior of a probability distribution beyond what is captured by the mean, i.e. average cryptocurrency returns, and the variance, i.e. their dispersion around the mean. Chung et al. (2006) suggest that in the absence of normality, investors should be very concerned with the shape of the tails of the distribution of portfolio returns, captured by higher-order moments. Skewness captures the distributional asymmetry, with positive skewness indicating a distribution with a tail on the right side that is longer than the left side and vice-versa. It is essential to study skewness anomalies because they would indicate return asymmetries and possible severe losses or gains. In addition, ignoring such anomalies may lead to a misinterpretation of the underlying

¹A market is efficient if market prices fully reflect all available information (MacDonald and Taylor, 1988).

distribution’s shape. Since kurtosis measures the tail heaviness of a distribution, it shows that outliers exist in the tails, indicating more extreme returns than a normal distribution, a typical feature of several financial series (Brooks and Henry, 2002; Dufour et al., 2003). Furthermore, ignoring these higher moments’ anomalies may lead to inaccurate characterizations of the distribution, which can affect the robustness of the models and the accuracy of return predictions.

Our results show anomalies in the mean, variance, skewness, and kurtosis of these cryptocurrencies’ returns, which signifies that the cryptocurrency market tends to violate the Efficient Market Hypothesis. Our findings are relevant to the various stakeholders in the cryptocurrency market. Crypto market participants can also consider the state of crypto markets with respect to calendar anomalies for their decision-making. Institutional and retail traders can build diversified portfolios of different cryptocurrencies using seasonal statistics and devise strategies based on seasonal patterns of a given cryptocurrency. Analysts can use our results to inform the choice of distribution and model specification when analyzing cryptocurrency returns. As mentioned, higher-order moments are significant in cryptocurrency markets and should be given consideration when modeling cryptocurrency returns.

The remainder of this paper is organized as follow: Section 2 reviews the existing literature on calendar anomalies. Section 3 discusses our methodology, while Section 4 presents the results of the empirical analysis. Section 5 concludes the paper.

2 Literature review

Calendar anomalies studies aim at describing the tendency of financial assets to behave dissimilarly during different periods of the week, the month or the year. For instance, researchers have documented that returns tend to be higher in January in contrast to other months and observe different patterns across days of the week, within the day, beginning-of-quarter, end-of-quarter, beginning-of-year, and end-of-year, among

others. Most of these studies analyze volume and volatility as well as returns. We focus our review of the literature on calendar anomalies involving stock, commodity, and cryptocurrency markets.

Wachtel (1942) was the first to report calendar effects as a form of seasonality. He studied the monthly effect in the US stock market, which other researchers later elaborated on. Rozeff and Kinney Jr (1976) scrutinized the New York Stock Exchange from 1904 to 1974 and found seasonality in monthly rates of return with a distinct January effect on the equity market.

French (1980) in another study detected consistent negative returns on Mondays for S&P 500 returns from 1953 through 1977. He highlighted that the weekend effect was responsible for the negative Monday returns, not a general ‘closed-market’ effect. Gibbons and Hess (1981) showed that the daily seasonality is most evident on Mondays when there are consistently negative mean returns for stocks and below-average returns for T-bills. They further noted that market-adjusted returns exhibited a day-of-the-week effect.

Kohli and Kohers (1992) identified a week-of-the-month return effect in the S&P 500 index as a seasonal anomaly due to a previously unidentifiable and ongoing pattern. These results imply significant differences in weekly return patterns across the weeks of a month. Kim and Park (1994) reported abnormally high returns in three of the major stock markets in the US (NYSE, AMEX, and NASDAQ) on the trading days before the holidays. They also observed relevant holiday effects in the US and Japanese stock markets, given each country’s difference in holidays and institutions. Boudreaux (1995) investigated Denmark, France, Germany, Norway, Singapore/Malaysia, Spain, and Switzerland stock markets for monthly effects. They detected the monthly effects in almost all of these countries. They also confirmed the existence of a January effect and a monthly effect in the US stock market.

Haug and Hirschey (2006) investigated the presence of the January effect in value-weighted returns for the years 1802-2004 and in equal-weighted returns for the years 1927-2004. Their results showed a persistent January effect for small-cap stocks. Similarly, Rompotis (2009) found that Greek equity funds experienced a highly depressive January effect on returns. Marrett and Worthington (2009) showed that the Australian market exhibited a pre-holiday effect common to small-cap stocks. Chia and Liew (2012) detected that from January 2000 to June 2009, the Japanese stock market experienced the November effect.

Fabozzi et al. (1994) found evidence of a holiday effect in futures commodities market. They observed significantly higher preholiday returns in futures contracts compared to nonholiday returns. Kohli (2014) singled out a DOW effect and January effect in crude oil returns in the period from 1983 through 2012. The research further indicated that there might be a daily seasonality in the variance of oil returns. Arendas (2017) showed that the Halloween effect was evident in the agricultural commodities markets. Qadan et al. (2019), in another study, observed within the commodity the presence of the Halloween effect, seasonal affective disorder (SAD)² effect, January effect, during-the-month effect, and start-of-the-month effect. Chhabra and Gupta (2022) investigated the calendar anomalies for the Indian commodity market and found that the calendar anomalies have been more prevalent in energy-based commodities than metals. Meek and Hoelscher (2023) investigated the DOW effect for petroleum and related products. They observed that the DOW effect varies across energy commodities. For instance, oil future return showed a negative Monday but a positive Wednesday return. They noted that when oil prices close higher on Friday, equity prices for energy companies the following Monday may be higher.

Studying the market efficiency of Bitcoin, Urquhart (2016) showed that the Bitcoin market was not inefficient during the entire sample period (August 2010 - July 2016).

²SAD refers to the seasonal variation in stock returns, which is linked to the depression caused by shorter days in the fall and winter.

Nadarajah and Chu (2017) used the simple power transformation of the Bitcoin returns to study the efficiency of crypto markets. They concluded that Bitcoin returns do not support the efficient market hypothesis. In further studies, Aharon and Qadan (2019) used OLS and GARCH models to analyze anomalies in Bitcoin returns. They reported evidence of the DOW effect on Bitcoin at the mean and variance levels for data from 2010–2017.

According to Baur et al. (2019), there existed time-specific anomalies in Bitcoin returns but they were not persistent for DOW and MOY, suggesting that investors could exploit these anomalies, reducing or eliminating them. According to Ma and Tanizaki (2019), the Bitcoin return and volatility were affected by the DOW effect. Kaiser (2019) tests for seasonality patterns in cryptocurrency returns, volatility, trading volume, and a spread estimator. The author observed that cryptocurrency returns do not have consistent and robust calendar effects and concluded that cryptocurrencies experience weak-form market efficiency. Caporale and Plastun (2019) investigated the day-of-the-week effect in the cryptocurrency market and detected no anomalies except for Bitcoin, for which returns on Mondays were significantly higher than those on the other days of the week. Kinateder and Papavassiliou (2021) examined Bitcoin returns for Halloween effects, DOW effect and MOY effects for the period between 2013-2019. They did not find a Halloween effect or DOW effect in Bitcoin return, but they identified the January effect. In a recent study, Naz et al. (2023) examined the day-of-the-week and January effects on cryptocurrencies with the highest capitalization. The results indicated that the Monday effect in the daily analysis generated a positive and significant coefficient for the considered currencies.

Similar to Urquhart (2016); Nadarajah and Chu (2017); Aharon and Qadan (2019); Baur et al. (2019); Caporale and Plastun (2019); Ma and Tanizaki (2019); Kaiser (2019); Kinateder and Papavassiliou (2021); Naz et al. (2023), we study calendar effects in cryptocurrency market. A novelty of the present study is that calendar anomalies are

investigated not just for Bitcoin but for several cryptocurrencies. We have only found the study by Caporale and Plastun (2019) that considers Bitcoin, Litecoin, Ripple and Dash. However, while these authors focus only on the day-of-the-week anomalies, we broaden the perspective to include the month-of-the-year, the quarter-of-the-year, the US Holidays and Weekend calendar effects. Additionally and foremost, we are the first to study anomalies in higher moments (skewness and kurtosis) for the returns of the considered cryptocurrencies. The inclusion of higher moments is crucial since they offer insights into the shape and behavior of a probability distribution beyond what is seized by mean and variance; this means that in addition to average returns and volatility anomalies, also the asymmetries in return gains and losses and the occurrence of extreme returns are taken into account.

3 Methodology

We compute returns at time t , x_t , as the logarithmic change in daily closing prices (P) of a given cryptocurrency:

$$x_t = \log(P_t) - \log(P_{t-1}) \quad (1)$$

and consider the following Autoregressive Conditional Density (ACD) model:

$$x_t = \mu_t + \varepsilon_t = \mu_t + \sigma_t z_t \quad (2)$$

with $z_t \sim JSU(0, 1, \xi_t, \eta_t)$, where *JSU* denotes the reparameterized Johnson's SU distribution presented in Appendix A. The skew parameter ξ_t controls the asymmetry of the distribution, whereas η_t controls the thickness of the tail. We present in equations (3a)–(3d) the dynamics for the (transformed) parameters determining the mean (μ_t), variance (σ_t^2), skewness (ξ_t), and kurtosis (λ_t):

$$\mu_t = \mu + \sum_{i=1}^P \phi_i x_{t-i} + \sum_{j=1}^Q \delta_j \varepsilon_{t-j} \quad (3a)$$

$$\sigma_t^2 = q_t + \sum_{j=1}^q \alpha_j (\varepsilon_{t-j}^2 - q_{t-j}) + \sum_{j=1}^p \beta_j (\sigma_{t-j}^2 - q_{t-j}) \quad (3b)$$

$$\xi_t = c_1 + a_1 |z_{t-1}| I_{z_{t-1} < 0} + g_1 |z_{t-1}| I_{z_{t-1} \geq 0} + b_1 \xi_{t-1} \quad (3c)$$

$$\lambda_t = \log(\eta_t) = c_2 + a_2 z_{t-1} + g_2 z_{t-1}^2 + b_2 \lambda_{t-1}. \quad (3d)$$

For the mean equation, we adopt an ARMA(P, Q), with the order of the model established using the Bayesian Information Criteria (BIC). For the variance equation, we consider the component GARCH model of Lee and Engle (1999). In the Lee and Engle (1999) model, the conditional variance is decomposed into a permanent and transitory component capturing the long- and short-run movements in volatility, respectively. In equation (3b), the permanent component of the conditional variance is specified as:

$$q_t = \omega - \rho q_{t-1} + \phi(\varepsilon_{t-1}^2 - \sigma_{t-1}^2) \quad (4)$$

where σ_{t-j}^2 is the lagged conditional variance and q_{t-j} its trend. The difference $\sigma_{t-j}^2 - q_{t-j}$ is the transitory component of the conditional variance. For the stationarity conditions to hold, the sum of the (α, β) coefficients in equation (3b) should be less than 1 and that $\rho < 1$ in equation (4).

In the case of the equation for the law of motion of the parameter ξ that determines the skewness of the distribution, we use a piece-wise linear model (equation 3c) as in Jondeau and Rockinger (2003). In equation (3c) and in the rest of this study, I_A denotes the indicator function, taking on value 1 if A is true, 0 otherwise. Finally, for the parameter determining the kurtosis of the distribution, we model its logarithm, $\lambda = \log(\eta)$ so that the positivity constraint is satisfied for all t and model λ using a quadratic specification (equation 3d) as in Hansen (1994).

Our strategy to assess whether there are calendar effects affecting one of the first four moments of each cryptocurrency distribution involves adding dummies to equations (3a)–(3d). Specifically, we estimate the ACD model of equations (3a)–(3d) and add a dummy variable only to a specific equation. As an example, when investigating calendar effects in the skewness, we keep (3a), (3b), and (3d) as above and only change (3c) as follows:

$$\xi_t = c_1 + a_1 |z_{t-1}| I_{z_{t-1} < 0} + g_1 |z_{t-1}| I_{z_{t-1} \geq 0} + b_1 \xi_{t-1} + d' D_{t,c}$$

where $D_{t,c}$ represent the time- t value of the dummy variables capturing a given calendar effect. The calendar effects we consider are listed in Table 1.

Table 1: List of Calendar Effects.

Calendar Effect	Description
Day Of The Week (DOW)	Dummies for days Monday to Sunday
Month Of The Year (MOY)	Dummies for months January to December
Quarter Of The Year (QOY)	Dummies for Q1 to Q4
Weekend	Dummies “SaturdayOrSunday”
Holiday	Dummies “Holiday”

Note: In the case of the Holiday calendar effect, we consider holidays in the United States.

4 Empirical Analysis

4.1 Data Description

We use daily closing prices for six cryptocurrencies to calculate daily returns. Our analysis covers the period ranging from August 8, 2015, to September 30, 2023. We have collected data for Bitcoin, Dash, Dogecoin, Litecoin, Ripple, and Stellar from coinMarketCap.com. Since cryptocurrencies trade seven days a week, we analyze $T = 2,976$ returns for each cryptocurrency. We present descriptive statistics in Table 2 for the selected cryptocurrencies. Figure 1 and Figure 2 sketch the return dynamics

of each cryptocurrency and density plots, respectively. In detail, Table 2 indicates that cryptocurrency returns have positive mean values, higher for Ripple, Bitcoin and Dogecoin than Stellar, Litecoin and Dash, and high standard deviations, suggesting dispersion in volatility across the six cryptocurrencies, with Ripple having the most considerable value. The data shows that Bitcoin returns are negatively skewed, denoting that this cryptocurrency experiences frequent modest gains and a few severe losses (Algieri and Leccadito, 2019). We also identify the presence of excess kurtosis in all cryptocurrencies, especially for Ripple and Dogecoin, and we can visually detect outliers in Figure 2. The zero p-values of the Jarque-Bera test show that returns do not conform to bell-shaped Gaussian distributions, i.e. cryptocurrency returns are not normally distributed and this is confirmed by the density plots reported in Figure 2. Tables 3–7 present instead descriptive statistics for DOW, MOY, QOY, the US Holiday, and Weekend effects. In the case of the mean, reported in the first panel of each table, we present $\hat{\mu}_{D_c} = \frac{1}{\sum_{t=1}^T I_{D_{t,c}=1}} \sum_{t=1}^T x_t I_{D_{t,c}=1}$, where $D_{t,c}$ is the dummy variable capturing a given calendar effect. The variance is calculated as $\hat{\sigma}_{D_c}^2 = \frac{1}{\sum_{t=1}^T I_{D_{t,c}=1}} \sum_{t=1}^T (x_t - \hat{\mu}_{D_c})^2 I_{D_{t,c}=1}$ and skewness and kurtosis are calculated in a similar way. Table 3 shows that Bitcoin has a negative mean return on Thursday and Sunday. The table further reveals that the Bitcoin returns are negatively skewed except for Monday, meaning that there is a higher probability of significant negative returns and small gains during all the other days of the week. Considering the tail, the results show that Bitcoin returns have a fat tail implying extreme return risk.

Table 2: Descriptive Statistics for Daily Log-returns of Cryptocurrencies

	Bitcoin	Dash	Dogecoin	Litecoin	Ripple	Stellar
Mean	0.0015	0.0007	0.0014	0.0009	0.0020	0.0013
Standard Deviation	0.0377	0.0571	0.0648	0.0534	0.0711	0.0674
Median	0.0015	0.0002	-0.0017	-0.0002	-0.0008	-0.0016
Minimum	-0.4647	-0.4655	-0.6163	-0.4491	-0.5151	-0.4100
Maximum	0.2251	0.4513	1.0274	0.5114	1.5164	0.7231
Standard Error	0.0007	0.0010	0.0012	0.0010	0.0013	0.0012
Skewness	-0.7490	0.3599	2.1899	0.2898	4.2267	1.9492
Kurtosis	14.5331	12.3677	40.1637	14.5822	84.5862	22.9973
Jarque-Bera	16771.9173	10945.6337	173640.4181	16676.0117	834242.4603	51471.2115
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

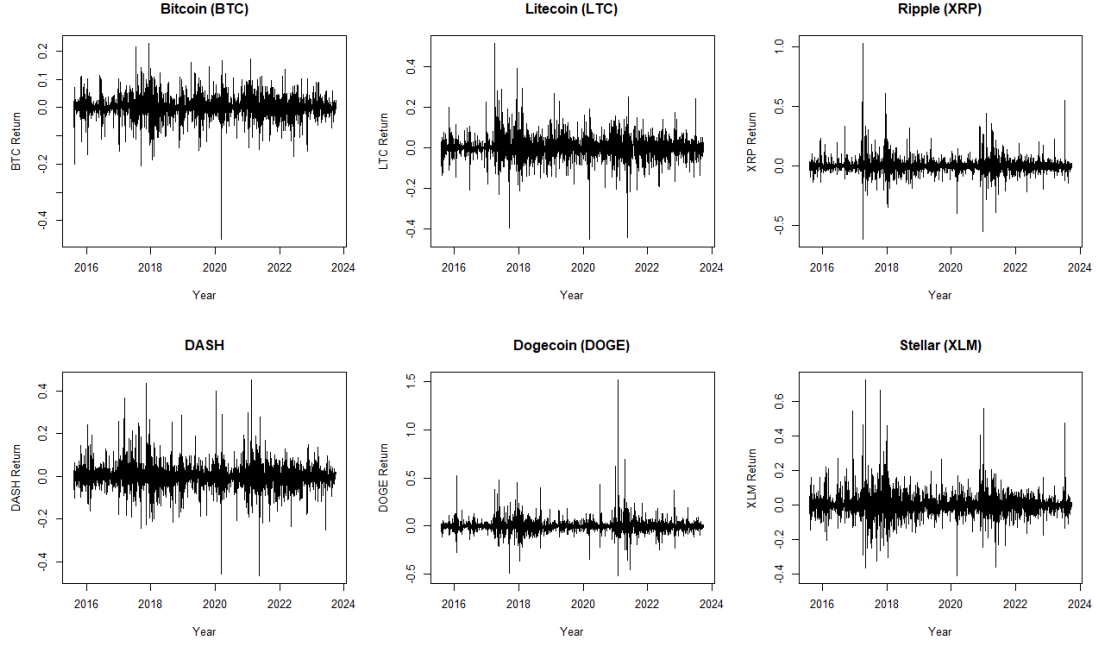


Figure 1: Plot of Cryptocurrencies Log Returns.

Note: Data spans from August 8, 2015, to September 30, 2023

4.2 Discussion of the Results

In Table 8, we present the results for the DOW effect in the mean, variance, skewness, and kurtosis equations for each cryptocurrency. Considering the mean equation for the DOW effect, we observe a Tuesday, Friday, and Saturday effect for Bitcoin and a Friday effect for Litecoin and Dash. Dogecoin displays a Monday, Friday, and Saturday effect, while Ripple and Stellar returns show a Thursday effect. This would suggest that the average returns of all cryptocurrencies, except for Ripple and Stellar, are higher on Fridays. Dogecoin tends to experience negative returns on Mondays, while Ripple and Stellar record negative “blue” returns on Thursdays. Our results for Bitcoin differ from Aharon and Qadan (2019), Ma and Tanizaki (2019) and Caporale and Plastun (2019), who detected a day-of-the-week effect on Monday, suggesting significantly higher mean return at the start of the week than other weekdays, but it is more in line with Bush et al. (2020).

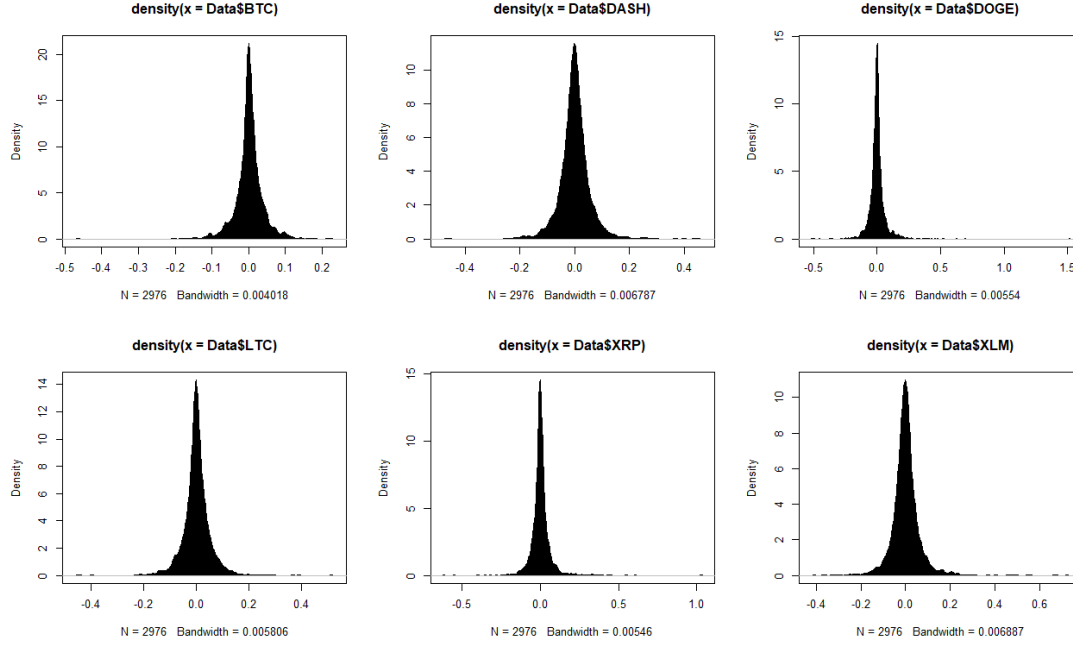


Figure 2: Density Plot of Cryptocurrencies Log Returns.

Note: Data spans from August 8, 2015, to September 30, 2023

The variance equation, which provides an indication of the cryptocurrency's volatility, suggests that Dash and Dogecoin show a Monday effect (higher volatility) and Litecoin a Thursday effect. We do not find DOW anomalies in the variance of Bitcoin, Ripple, and Stellar returns.

The estimated skewness equation, which gives information about the asymmetries in the returns, shows that Bitcoin does not show a DOW effect, i.e. it is not possible to spot any systematic pattern regarding any likely abnormal value in the third moment of the distribution. We observe a Thursday effect in Dash, Ripple, and Stellar's return, suggesting that, tendentially, these cryptocurrencies record frequent small losses and a few extreme gains on Thursdays. The same pattern is recorded for Dash and Dogecoins on Sundays. Litecoin and Ripple tend instead to experience recurrent abnormal level of skewness on Saturdays and Wednesdays, respectively.

The estimated kurtosis equation, which reveals the probability of experiencing ex-

Table 3: Descriptive Statistics, DOW Effect

	Bitcoin	Dash	Dogecoin	Litecoin	Ripple	Stellar
Mean $\hat{\mu}_{D_c}$						
Monday	0.0035	-0.0025	-0.0023	-0.0018	-0.0006	0.0020
Tuesday	0.0013	-0.0014	0.0000	0.0021	0.0011	0.0015
Wednesday	0.0021	0.0029	0.0013	-0.0008	-0.0014	-0.0002
Thursday	-0.0002	-0.0011	0.0026	-0.0035	0.0036	-0.0026
Friday	0.0017	0.0027	0.0043	0.0046	0.0055	0.0030
Saturday	0.0024	0.0037	0.0075	0.0063	0.0010	0.0048
Sunday	-0.0001	0.0007	0.0006	-0.0005	0.0006	0.0006
Variance $\hat{\sigma}_{D_c}^2$						
Monday	0.0016	0.0033	0.0039	0.0029	0.0048	0.0048
Tuesday	0.0014	0.0028	0.0041	0.0028	0.0038	0.0050
Wednesday	0.0015	0.0044	0.0043	0.0037	0.0042	0.0055
Thursday	0.0023	0.0038	0.0100	0.0039	0.0065	0.0052
Friday	0.0014	0.0025	0.0044	0.0031	0.0035	0.0040
Saturday	0.0009	0.0031	0.0051	0.0019	0.0024	0.0035
Sunday	0.0008	0.0030	0.0035	0.0016	0.0041	0.0038
Skewness $\hat{\mu}_{3,D_c}$						
Monday	0.0133	0.0369	-0.4775	0.5921	-0.9618	2.3037
Tuesday	-0.7867	0.0893	0.9832	0.9754	0.5654	1.1918
Wednesday	-0.1413	0.0477	0.6918	-0.3871	-1.6575	1.2780
Thursday	-1.9138	-0.7813	8.0543	-0.0710	2.6291	0.5069
Friday	-0.1357	-0.2308	3.2593	0.5856	2.3929	1.7158
Saturday	-0.1923	2.0295	1.9657	1.2680	2.7110	3.7711
Sunday	-0.2677	1.8522	2.3807	0.0038	9.9447	4.6476
Kurtosis $\hat{\mu}_{4,D_c}$						
Monday	6.1863	6.2081	11.6118	9.6903	22.5602	24.5955
Tuesday	7.8060	6.4168	16.9232	12.7437	11.5831	16.7589
Wednesday	6.1888	13.8149	11.6872	12.8703	18.8534	15.7204
Thursday	25.8294	12.1246	126.5007	22.3874	20.3143	11.5924
Friday	5.7936	4.9604	35.0872	7.2616	17.9070	14.6747
Saturday	7.4936	19.4319	28.6647	10.3004	26.8430	43.6662
Sunday	6.1495	16.0683	19.3824	5.9224	157.7111	53.3472

Note: This table reports, for each cryptocurrency, $\hat{\mu}_{D_c} = \frac{1}{T_{D_c}} \sum_{t=1}^T I_{D_{t,c}=1}$,

$$\hat{\sigma}_{D_c}^2 = \frac{1}{T_{D_c}} \sum_{t=1}^T (x_t - \hat{\mu}_{D_c})^2 I_{D_{t,c}=1}, \hat{\mu}_{3,D_c} = \frac{1}{T_{D_c}} \sum_{t=1}^T \left(\frac{x_t - \hat{\mu}_{D_c}}{\hat{\sigma}_{D_c}} \right)^3 I_{D_{t,c}=1}, \text{ and}$$

$$\hat{\mu}_{4,D_c} = \frac{1}{T_{D_c}} \sum_{t=1}^T \left(\frac{x_t - \hat{\mu}_{D_c}}{\hat{\sigma}_{D_c}} \right)^4 I_{D_{t,c}=1}, \text{ where } T_{D_c} = \sum_{t=1}^T I_{D_{t,c}=1} \text{ and } D_{t,c} \text{ is the dummy DOW at time } t.$$

treme returns, shows the Tuesday, Wednesday, and Friday effects in Bitcoin return, with the highest likelihood of experiencing severe tail events on Fridays.. We do not find a DOW effect for Dash and Litecoin. We detect Thursday, Friday, and Saturday effects in Dogecoin return. Ripple returns show Tuesday, Thursday, and Saturday effects, with the highest probability of registering strong tail events on Saturdays. For Stellar, we observe that all the days of the week dummies are significant and the highest risk of

Table 4: Descriptive Statistics, MOY Effect

	Bitcoin	Dash	DOGE	Litecoin	Ripple	Stellar
Mean $\hat{\mu}_{D_m}$						
January	-3.17e-05	0.0045	0.0092	0.0002	0.0005	0.0048
February	0.0037	0.0056	-0.0006	0.0034	-0.0009	-0.0020
March	-0.0010	0.0036	-0.0017	0.0002	0.0045	0.0004
April	0.0040	0.0028	0.0154	0.0068	0.0086	0.0065
May	0.0015	-0.0018	0.0028	0.0009	0.0029	0.0054
June	-0.0003	-0.0046	-0.0033	-0.0015	-0.0043	-0.0046
July	0.0029	0.0006	-0.0013	0.0003	0.0005	0.0010
August	-0.0002	0.0013	0.0010	-0.0032	0.0000	-0.0014
September	-0.0013	-0.0034	-0.0037	-0.0026	0.0012	-0.0021
October	0.0061	-0.0019	0.0028	0.0022	-0.0009	0.0029
November	0.0007	0.0025	-0.0011	0.0027	0.0009	0.0027
December	0.0030	0.0002	0.0050	0.0029	0.0035	0.0020
Variance $\hat{\sigma}_{D_m}^2$						
January	0.0018	0.0053	0.0178	0.0027	0.0042	0.0060
February	0.0015	0.0044	0.0042	0.0031	0.0030	0.0029
March	0.0023	0.0051	0.0024	0.0036	0.0043	0.0031
April	0.0009	0.0028	0.0079	0.0028	0.0101	0.0040
May	0.0015	0.0045	0.0067	0.0048	0.0061	0.0101
June	0.0018	0.0023	0.0034	0.0032	0.0024	0.0031
July	0.0013	0.0019	0.0037	0.0018	0.0028	0.0042
August	0.0010	0.0027	0.0026	0.0016	0.0022	0.0020
September	0.0011	0.0023	0.0036	0.0029	0.0032	0.0035
October	0.0006	0.0010	0.0019	0.0011	0.0014	0.0050
November	0.0016	0.0039	0.0031	0.0028	0.0031	0.0046
December	0.0017	0.0032	0.0035	0.0040	0.0080	0.0063
Skewness $\hat{\mu}_{3,D_m}$						
January	-0.8818	0.9324	6.1209	-0.4973	0.7272	2.2486
February	0.1148	1.1560	1.4752	0.9097	-0.5539	-0.1065
March	-3.4955	0.0450	-1.0795	0.8459	1.4521	-1.2968
April	0.8756	0.1641	2.5677	1.0257	3.7471	1.3606
May	-0.2015	-1.2811	0.6604	-0.8565	0.2732	2.6382
June	-0.6245	-0.6679	-1.6992	0.4758	0.6539	0.2257
July	0.8352	0.2234	1.6578	0.4238	4.4437	1.4643
August	-0.9788	1.0924	2.5148	0.0822	1.1148	0.4756
September	-1.0327	-1.3424	-1.6353	-1.7748	1.2299	-0.3468
October	1.2063	0.1113	3.1064	1.4927	-0.1304	3.6986
November	-0.4504	1.3340	0.3530	-0.0450	1.4002	1.3602
December	0.8789	0.6399	2.0066	2.0976	1.7385	2.1475
Kurtosis $\hat{\mu}_{4,D_m}$						
January	6.3748	8.2984	69.7644	6.0694	18.2007	18.7897
February	6.8246	11.6866	10.3547	8.5924	7.2866	5.8667
March	37.0541	13.1870	13.7867	34.8098	21.5748	15.3220
April	7.9133	4.6426	19.5172	7.8770	51.4209	15.7956
May	4.9776	13.5475	10.4673	11.4335	9.0113	23.2215
June	4.9344	7.9620	18.0161	8.0862	11.8972	6.9478
July	9.0525	6.7293	14.2756	4.6741	48.6971	15.2006
August	9.4841	7.8278	18.8748	5.1324	8.4386	4.3103
September	12.1021	9.4592	23.3684	15.3721	12.5786	9.2234
October	8.4935	5.9045	24.7885	11.8093	6.8114	35.9730
November	5.3327	13.2577	7.8548	4.1082	14.0764	10.7267
December	8.0736	7.9804	17.6481	13.4828	21.4262	14.0087

Note: This table reports, for each cryptocurrency, $\hat{\mu}_{D_m} = \frac{1}{T_{D_m}} \sum_{t=1}^T I_{D_{t,m}=1}$,

$$\hat{\sigma}_{D_m}^2 = \frac{1}{T_{D_m}} \sum_{t=1}^T (x_t - \hat{\mu}_{D_m})^2 I_{D_{t,m}=1}, \hat{\mu}_{3,D_m} = \frac{1}{T_{D_m}} \sum_{t=1}^T \left(\frac{x_t - \hat{\mu}_{D_m}}{\hat{\sigma}_{D_m}} \right)^3 I_{D_{t,m}=1}, \text{ and}$$

$$\hat{\mu}_{4,D_m} = \frac{1}{T_{D_m}} \sum_{t=1}^T \left(\frac{x_t - \hat{\mu}_{D_m}}{\hat{\sigma}_{D_m}} \right)^4 I_{D_{t,m}=1}, \text{ where } T_{D_m} = \sum_{t=1}^T I_{D_{t,m}=1} \text{ and } D_{t,m} \text{ is the dummy MOY at time } t.$$

extreme events is on the weekend, especially on Saturdays.

Table 9 presents the MOY effect for each cryptocurrency. We observe anomalies in the mean of Bitcoin returns in April and October, Dash in October, Ripple in December, and Stellar in August and December. In particular, the average returns are higher for

Table 5: Descriptive Statistics, QOY Effect

	Bitcoin	Dash	DOGE	Litecoin	Ripple	Stellar
Mean $\hat{\mu}_{D_q}$						
Q1	0.0008	0.0045	0.0024	0.0012	0.0014	0.0012
Q2	0.0017	-0.0012	0.0049	0.0020	0.0024	0.0025
Q3	0.0004	-0.0005	-0.0014	-0.0019	0.0006	-0.0009
Q4	0.0033	0.0002	0.0022	0.0026	0.0012	0.0025
Variance $\hat{\sigma}_{D_q}^2$						
Q1	0.0019	0.0049	0.0083	0.0031	0.0038	0.0040
Q2	0.0014	0.0032	0.0060	0.0036	0.0062	0.0058
Q3	0.0011	0.0023	0.0033	0.0021	0.0027	0.0032
Q4	0.0013	0.0027	0.0028	0.0026	0.0041	0.0053
Skewness $\hat{\mu}_{3,D_q}$						
Q1	-1.8887	0.6757	6.9008	0.5002	0.7593	1.1446
Q2	-0.2610	-0.8129	1.3747	-0.1080	2.8183	2.4159
Q3	-0.2541	0.0713	0.5876	-0.8523	2.2652	0.6558
Q4	0.3322	1.0946	1.6498	1.4459	1.8959	2.4350
Kurtosis $\hat{\mu}_{4,D_q}$						
Q1	22.4599	11.0358	114.5941	20.0836	18.0947	18.8640
Q2	5.8140	11.6576	18.0262	10.6366	49.5222	27.6443
Q3	10.4371	8.4975	19.5626	12.0342	23.8907	12.7398
Q4	7.9494	13.3406	16.1541	12.7320	29.6279	20.0558

Note: This table reports, for each cryptocurrency, $\hat{\mu}_{D_q} = \frac{1}{T_{D_q}} \sum_{t=1}^T I_{D_{t,q}=1}$,

$$\hat{\sigma}_{D_q}^2 = \frac{1}{T_{D_q}} \sum_{t=1}^T (x_t - \hat{\mu}_{D_q})^2 I_{D_{t,q}=1}, \hat{\mu}_{3,D_q} = \frac{1}{T_{D_q}} \sum_{t=1}^T \left(\frac{x_t - \hat{\mu}_{D_q}}{\hat{\sigma}_{D_q}} \right)^3 I_{D_{t,q}=1}, \text{ and}$$

$$\hat{\mu}_{4,D_q} = \frac{1}{T_{D_q}} \sum_{t=1}^T \left(\frac{x_t - \hat{\mu}_{D_q}}{\hat{\sigma}_{D_q}} \right)^4 I_{D_{t,q}=1}, \text{ where } T_{D_q} = \sum_{t=1}^T I_{D_{t,q}=1} \text{ and } D_{t,q} \text{ is the dummy QOY at time } t.$$

Bitcoins in April and October and lower for Dash in October, Ripple and Stellar in December, and Stellar in August. We do not find MOY anomalies in the means of Dogecoin and Litecoin returns. In any case, for all cryptocurrencies and differently from the stock market, there is no evidence of a “January effect”.

Moreover, there are no systematic patterns in the volatility for Bitcoin in the months of the year. Instead, the variance equation of Dash shows anomalies, i.e. higher return volatility, in February, and Dogecoin in January, March, and July. We also observe anomalies in the variance of Litecoin and Stellar returns in July, October, and December and in January, August, October, and December for Ripple.

We do not single out a MOY anomaly in the skewness of Bitcoin, Dogecoin, Ripple, and Stellar returns. Instead, we document anomalies with likely large jumps in October

Table 6: Descriptive Statistics Holiday Effect

	Bitcoin	Dash	DOGE	Litecoin	Ripple	Stellar
Mean $\hat{\mu}_{D_h}$						
NoHoliday	0.0015	0.0007	0.0020	0.0009	0.0014	0.0013
Holiday	0.0162	-0.0088	0.0093	0.0194	0.0176	-0.0114
Variance $\hat{\sigma}_{D_h}^2$						
NoHoliday	0.0014	0.0033	0.0051	0.0028	0.0042	0.0045
Holiday	0.0044	0.0013	0.0007	0.0031	0.0016	0.0008
Skewness $\hat{\mu}_{3,D_h}$						
NoHoliday	-0.7588	0.3592	4.2224	0.2897	2.1900	1.9463
Holiday	0.0648	-0.1522	0.7341	0.3061	0.3785	0.3279
Kurtosis $\hat{\mu}_{4,D_h}$						
NoHoliday	14.6187	12.3512	84.4045	14.5984	40.1222	22.9496
Holiday	1.4657	0.8850	1.9387	1.2156	1.5662	1.2112

Note: This table reports, for each cryptocurrency, $\hat{\mu}_{D_h} = \frac{1}{T_{D_h}} \sum_{t=1}^T I_{D_{t,h}=1}$,

$\hat{\sigma}_{D_h}^2 = \frac{1}{T_{D_h}} \sum_{t=1}^T (x_t - \hat{\mu}_{D_h})^2 I_{D_{t,h}=1}$, $\hat{\mu}_{3,D_h} = \frac{1}{T_{D_h}} \sum_{t=1}^T \left(\frac{x_t - \hat{\mu}_{D_h}}{\hat{\sigma}_{D_h}} \right)^3 I_{D_{t,h}=1}$, and $\hat{\mu}_{4,D_h} = \frac{1}{T_{D_h}} \sum_{t=1}^T \left(\frac{x_t - \hat{\mu}_{D_h}}{\hat{\sigma}_{D_h}} \right)^4 I_{D_{t,h}=1}$, where $T_{D_h} = \sum_{t=1}^T I_{D_{t,h}=1}$ and $D_{t,h}$ is the dummy U.S. Holidays at time t .

Table 7: Descriptive Statistics Weekend Effect

	Bitcoin	Dash	DOGE	Litecoin	Ripple	Stellar
Mean $\hat{\mu}_{D_w}$						
MonToFriday	0.0017	0.0001	0.0012	0.0001	0.0016	0.0007
SatSun	0.0012	0.0022	0.0040	0.0029	0.0008	0.0027
Variance $\hat{\sigma}_{D_w}^2$						
MonToFriday	0.0017	0.0034	0.0053	0.0033	0.0046	0.0049
SatSun	0.0008	0.0030	0.0043	0.0018	0.0033	0.0036
Skewness $\hat{\mu}_{3,D_w}$						
MonToFriday	-0.8085	-0.1780	4.8074	0.2341	0.7898	1.3572
SatSun	-0.2276	1.9448	2.1675	0.7167	7.8773	4.2388
Kurtosis $\hat{\mu}_{4,D_w}$						
MonToFriday	14.3382	10.4788	98.7522	14.3743	20.4727	16.8096
SatSun	6.8447	17.8275	26.6089	8.6390	132.0155	48.9787

Note: This table reports, for each cryptocurrency, $\hat{\mu}_{D_w} = \frac{1}{T_{D_w}} \sum_{t=1}^T I_{D_{t,w}=1}$,

$\hat{\sigma}_{D_w}^2 = \frac{1}{T_{D_w}} \sum_{t=1}^T (x_t - \hat{\mu}_{D_w})^2 I_{D_{t,w}=1}$, $\hat{\mu}_{3,D_w} = \frac{1}{T_{D_w}} \sum_{t=1}^T \left(\frac{x_t - \hat{\mu}_{D_w}}{\hat{\sigma}_{D_w}} \right)^3 I_{D_{t,w}=1}$, and $\hat{\mu}_{4,D_w} = \frac{1}{T_{D_w}} \sum_{t=1}^T \left(\frac{x_t - \hat{\mu}_{D_w}}{\hat{\sigma}_{D_w}} \right)^4 I_{D_{t,w}=1}$, where $T_{D_w} = \sum_{t=1}^T I_{D_{t,w}=1}$ and $D_{t,w}$ is the dummy U.S. Holidays at time t .

for Litecoin's return and mainly in February for Dash's returns. The kurtosis equation shows several significant risks of tail events, especially for Dogecoin, Stellar and Litecoin, pointing to the high likelihood of experiencing dramatic changes in their returns. The

Table 8: Estimate Day of the Week Effect

Mean Equation	Bitcoin	Dash	Dogecoin	Litecoin	Ripple	Stellar
Monday	0.0012	-0.0008	-0.0023*	-0.0015	-0.0012	-0.0012
Tuesday	0.0031**	-0.0018	-0.0010	0.0011	-0.0011	-0.0021
Wednesday	0.0003	0.0009	-0.0013	-0.0006	-0.0003	-0.0026
Thursday	0.0003	-0.0031	-0.0021	-0.0001	-0.0038***	-0.0037**
Friday	0.0020**	0.0042*	0.0037***	0.0026*	0.0009	0.0022
Saturday	0.0013*	0.0024	0.0018*	0.0016	0.0001	0.0023
Sunday	0.0005	-0.0027	-0.0014	-0.0009	-0.0017	-0.0005
Variance Equation						
Monday	2e-04	6e-04**	4e-04*	1.71e-07	3e-04	2.49e-05
Tuesday	2.85e-07	6.77e-08	1.69e-05	7.03e-08	6.85e-08	3.01e-05
Wednesday	3.52e-08	2.57e-08	7.86e-06	7.87e-08	1.30e-07	2.43e-08
Thursday	1.12e-08	3.18e-08	2.16e-07	2.07e-06**	2.33e-08	1.93e-08
Friday	2.08e-09	2.58e-09	1.98e-08	8.67e-10	6.83e-09	2.05e-09
Saturday	2.79e-11	4.43e-13	5.61e-13	1.30e-12	1.33e-18	6.90e-12
Sunday	1.84e-08	5.00e-08	3.55e-08	4.86e-08	1.42e-08	2.44e-08
Skewness Equation						
Monday	0.0021	-0.0308	0.0446***	0.0216	0.0143	0.0094
Tuesday	-0.0119	-0.0077	0.0062	-0.0023	0.0124	0.0110*
Wednesday	0.0004	-0.0275	0.0064	0.0001	-0.0254*	0.0025
Thursday	0.0002	0.0479**	0.0319	0.0088	0.0337**	0.0411**
Friday	0.0028	-0.0254	-0.0211	-0.0114	0.0190	0.0156
Saturday	-0.0054	-0.0287	-0.0053	-0.0141**	0.0061	-0.0436
Sunday	0.0118	0.0890***	0.0376**	0.0306	0.0224	0.0224
Kurtosis Equation						
Monday	0.1501	0.1878	0.0294	0.0005	0.2674	1.8373**
Tuesday	1.5715***	1.1652	0.3433	0.2351	1.4425*	1.8781***
Wednesday	1.5418**	0.9522	0.1468	0.1058	0.7156	1.7282**
Thursday	1.0532	0.9916	0.7032**	0.6106	1.6630*	2.3049***
Friday	1.9533***	0.8938	0.6845**	0.0162	1.2370	2.0873**
Saturday	7.6630	2.1048	1.0935***	1.1729	3.8102**	2.7475***
Sunday	0.0182	0.7984	0.0803	0.0050	0.6785	2.4920**

Note: *** = 1% significance, ** = 5% significance, * = 10% significance

more intense tail events are detected in September for Bitcoin, Dash and Litecoin, October for Dogecoin and Stellar, and June for Ripple.

We present in Table 10 the results concerning the QOY effect for the mean, variance, skewness, and kurtosis equations for each cryptocurrency. Our results show calendar effects in the 4th quarter of the year for Litecoin, Ripple, and Stellar. In particular, these cryptocurrencies systematically lessen their average returns in October, November and December. Conversely, Bitcoin tends to experience systematic positive returns especially in the 2nd quarter of the year. No calendar effects regarding average returns have been detected for Dash and Dogecoin. From the estimated variance equations, we

Table 9: Estimate the Month of the Year Effect

Mean Equation	Bitcoin	Dash	Dogecoin	Litecoin	Ripple	Stellar
January	0.0014	0.0037	-0.0012	9e-04	-0.0017	0.0023
February	0.0024	0.0033	-0.0014	9e-04	-0.0019	-0.0018
March	0.0013	0.0006	4e-04	0.0010	6e-04	0.0029
April	0.0031***	0.0004	0.0028	0.0010	1.10e-05	0.0012
May	0.0021	0.0014	-1e-04	0.0031	-0.0015	-0.0011
June	0.0015	-0.0016	3e-04	-2.36e-05	-5e-04	-0.0006
July	0.0001	0.0006	-0.0017	-0.0012	-4e-04	-0.0005
August	-0.0005	-0.0012	-9e-04	-0.0017	-0.0018	-0.0032**
September	0.0006	-0.0001	-2.66e-05	2e-04	-2.03e-05	-0.0004
October	0.0019*	-0.0022*	-4e-04	2e-04	-5e-04	-0.0004
November	0.0011	-0.0017	-9e-04	2e-04	-0.0011	-0.0028
December	0.0008	-0.0008	-9e-04	-9e-04	-0.0039* *	-0.0051***
Variance Equation						
January	0.0040	-0.0018	0.0386*	0.0100	0.0248***	0.0091
February	0.0033	0.0098***	0.0247	0.0273	0.0123	0.0053
March	-0.0083	0.0198	0.0303*	-0.0063	0.0162	0.0064
April	-0.0270	-0.0037	0.0093	0.0059	0.0074	-0.0202
May	-0.0187	-0.0125	0.0221	-0.0051	-0.0069	-0.0005
June	-0.0143	-0.0080	-0.0008	-0.0027	-0.0239	-0.0165
July	0.0228	0.0093	0.0303**	0.0481**	0.0143	0.0299*
August	0.0042	0.0001	0.0200	0.0164	0.0164* *	0.0200
September	0.0055	-0.0168	0.0032	0.0092	0.0044	0.0091
October	0.0295	0.0188	0.0243	0.0498*	0.0023***	0.0389*
November	-0.0128	0.0217	0.0199	0.0192	-0.0059	0.0176
December	0.0182	0.0118	0.0265	0.0343**	0.0357**	0.0284*
Skewness Equation						
January	4.20e-08	1e-04	1e-04	6.74e-09	1.39e-07	4.82e-08
February	3.38e-08	3e-04**	8.43e-08	3.50e-09	1.88e-08	2.34e-08
March	1.20e-09	2.32e-08	4.49e-07	4.89e-09	1.58e-08	5.66e-09
April	5.92e-07	1e-04	7.91e-09	2.45e-08	6.32e-09	1.62e-17
May	2.69e-07	1e-04	2.13e-11	1.96e-08	6.53e-13	1.75e-08
June	1.67e-08	1e-04	1.32e-05	4.01e-09	4.14e-09	1.11e-07
July	6.08e-09	1e-04	7.78e-09	1.53e-13	5.68e-09	1.25e-08
August	1.06e-08	1e-04	1.94e-07	1.72e-08	2.15e-08	5.74e-08
September	7.63e-16	3.66e-13	3.71e-05	5.67e-08	1e-04	1.29e-05
October	1.33e-05	1e-04*	7.43e-06	6.55e-06***	1.77e-07	2.73e-07
November	1.13e-07	1e-04*	2.56e-05	6.06e-09	2.53e-05	1.18e-07
December	4.03e-08	1e-04	1.06e-05	1.54e-08	1.33e-07	4.80e-08
Kurtosis Equation						
January	0.0748	0.0230	0.4591***	0.0435	0.1296*	1.6953***
February	0.0010	0.0025	0.3968**	0.0237	0.1124	1.3333***
March	0.1230***	0.0052	0.5190***	0.1002***	0.1810	1.6912***
April	7e-04	0.0211	0.4313***	0.0153	0.1140*	1.5582***
May	4.07e-05	0.0266	0.4771***	0.0550**	0.1204	1.6377***
June	0.0481	0.0154	0.5060***	0.0854***	0.2038**	1.6577***
July	0.0749*	0.0059	0.5837***	0.0504*	0.1163	1.8402***
August	0.0644	0.0290	0.5348***	0.0487*	0.1815	1.8636***
September	0.1342***	0.0483*	0.6348***	0.1276***	0.1494	1.7863***
October	7e-04	0.0005	0.6651***	0.0357	0.1338	2.0400***
November	0.0392	0.0184	0.4538**	0.0396	0.1014	1.8107***
December	0.0670	0.0022	0.4867***	0.0714**	0.1431	1.9770***

Note: *** = 1% significance, ** = 5% significance, * = 10% significance

identify anomalies in the 4th quarter of the year for Dash, in the 3rd and 4th quarters for Dogecoin, Litecoin, and Ripple, and in the 3rd quarter of the year for Stellar. Put differently, we identify the highest volatility, especially in the last quarter of the year, for all cryptocurrencies except for Bitcoin and Stellar. There are no calendar effects in volatility for Bitcoin returns, since the QOY effect in the Bitcoin's variance is never significant. For the skewness, Dash's return does not show any QOY anomaly. Instead, we observe relevant systematic asymmetries for Dogecoin and an anomaly in the 2nd

quarter of the year for Bitcoin returns. In particular, the negative skewness suggests that frequent small gains and a few utmost losses tend to occur for Bitcoin in the months of April, May and June. We observe the most substantial anomalies in the kurtosis in the 3rd quarter of the year for all cryptocurrencies, except for Stellar, which registers the highest anomalies in October, November and December and for Dogecoin, which does not disclose any tail anomaly.

Table 10: Estimate of the Quarter of the Year

Mean Equation	Bitcoin	Dash	Dogecoin	Litecoin	Ripple	Stellar
Q1	0.0016*	0.0025	-0.0006	-0.0010	-0.0010	0.0012
Q2	0.0024**	-1.65e-05	0.0008	-0.0008	-0.0008	-0.0002
Q3	0.0001	-3e-04	-0.0005	-0.0008	-0.0008	-0.0016
Q4	0.0014*	-0.0018	-0.0007	-0.0018*	-0.0018*	-0.0027***
Variance Equation						
Q1	1.81e-08	1.24e-07	1.33e-07	4.51e-08	4.51e-08	5.20e-08
Q2	4.30e-08	1.71e-13	1.28e-12	3.51e-11	3.51e-11	7.65e-07
Q3	9.11e-15	7.13e-06	1.18e-05***	8.91e-06***	8.91e-06***	9.55e-06*
Q4	8.40e-08	4.51e-05**	2.46e-05**	2.06e-05**	2.06e-05**	1.07e-05
Skewness Equation						
Q1	-0.0046	0.0056	0.0309***	0.0060	0.0164*	0.0059
Q2	-0.0201*	-0.0107	0.0078	-0.0065	-0.0064	-0.0154
Q3	0.0061	-0.0055	0.0142*	0.0090	0.0112	0.0211*
Q4	0.0043	0.0141	0.0206**	0.0210*	0.0101	0.0300**
Kurtosis Equation						
Q1	0.1112*	0.0122	0.4160	0.0619***	0.9568***	1.6276***
Q2	0.0229	0.0178	0.4251	0.0608***	0.9690***	1.6558***
Q3	0.1292*	0.0274***	0.5213	0.0842***	1.1114***	1.8480***
Q4	0.0524	0.0139	0.4677	0.0633***	0.8790***	1.9930***

Note: *** = 1% significance, ** = 5% significance, * = 10% significance
Q1 = 1st quarter, Q2 = 2nd quarter, Q3 = 3rd quarter, Q4 = 4th quarter

Table 11 displays the results of the Holiday effect in each market. We observe significant anomalies for Bitcoin and Ripple mean returns around holidays. We do not uncover any holiday anomalies in the mean returns of Dash, Dogecoin, Litecoin, and Stellar. The implication is that Bitcoin and Ripple prices tend to increase during holidays, especially Christmas and New Year's Day, due to increased demand from investors and traders. The estimated variance equations show the presence of calendar effects; that is, Bitcoin and Stellar are more volatile during the holidays. The estimated skewness and kurtosis equations show no asymmetric or extreme returns occurring for

any cryptocurrency during holidays.

Table 11: Estimate Holiday Effect

Mean Equation	Bitcoin	Dash	Dogecoin	Litecoin	Ripple	Stellar
Holiday	0.0024*	0.0045	0.0002	0.0042	0.0045*	0.0034
Variance Equation						
Holiday	1e-04***	7e-04	2.09e-13	6.02e-12	1.12e-07	2e-04***
Skewness Equation						
Holiday	-0.0200	-0.0111	0.0222	-0.0458	-0.0442	-0.0193
Kurtosis Equation						
Holiday	0.0293	1.61e-06	3.4364	0.0085	0.3740	1.3044

Note: *** = 1% significance, ** = 5% significance, * = 10% significance

To complete the analysis, we report the results for the Weekend effect in Table 12. We do not detect any anomaly in mean returns and volatility on the weekend days for all the cryptocurrencies except for Dash, which registers more volatility on Saturdays and Sundays. Instead, we document weekend anomalies in the kurtosis for all cryptocurrencies, excluding Litecoin. This finding highlights that returns' extremeness tends to materialise on the weekends.

Table 12: Estimate Weekend Effect

Mean Equation	Bitcoin	Dash	Dogecoin	Litecoin	Ripple	Stellar
SatSun	0.0009	-0.0002	0.0004	0.0004	-0.0007	0.0010
Variance Equation						
SatSun	2.72e-12	1e-04***	5.76e-12	3.82e-12	4.17e-12	7.11e-12
Skewness Equation						
SatSun	-0.0006	0.0192	0.0193	0.0193	0.0094	-0.0108
Kurtosis Equation						
SatSun	5.9875**	3.0167***	3.2487***	0.2386	3.9039***	2.6744***

Note: *** = 1% significance, ** = 5% significance, * = 10% significance

5 Conclusion

This study has investigated different types of calendar anomalies in the cryptocurrency market at higher moments. In particular, we have scrutinized the day-of-the-week, the month-of-the-year, the quarter-of-the-year, the US Holidays, and the Weekend calendar

anomalies for Bitcoin, Dash, Dogecoin, Litecoin, Ripple, and Stellar. For this purpose, we have employed the ACD model with dummy variables for the period 2015-2023. Our results suggest that the cryptocurrency market presents some *sfumato*, as the effect of Leonardo’s *Mona Lisa*³, and in some periods, it tends to violate the Efficient Market Hypothesis, hence creating an opportunity to earn abnormal returns.

In particular, almost all cryptocurrencies experience a calendar effect on Fridays, with mean returns above the average. Unlike stocks, all cryptocurrencies, excluding Dogecoin, do not exhibit significant Monday anomaly. No cryptocurrency registers any January effect, while Bitcoin shows an April and October effect with higher mean returns in these months. In terms of volatility, Dash and Dogecoin display marked return oscillations on Mondays, while Litecoin on Thursdays. The other cryptocurrencies do not show any DOW anomaly in the variance. Except for Bitcoin, we also found the DOW effect in the estimated skewness equations of the considered cryptocurrencies. We further observe anomalies in the kurtosis of Bitcoin, Dogecoin, Ripple, and Stellar returns. We find significant anomalies for Bitcoin and Ripple mean returns around holidays, while a higher probability of extreme returns for all cryptocurrencies characterizes weekends and, excluding Ripple, the months of September and October.

Our study holds significance for the diverse array of participants in the cryptocurrency market. Those engaged in the crypto market may find it valuable to consider calendar anomalies at higher moments to inform their decision-making. The insights from our study can aid investors in developing trading strategies to capitalize on abnormal returns and crafting risk management strategies. Both institutional and retail traders have the opportunity to construct diversified portfolios of various cryptocurrencies by leveraging seasonal information, thereby formulating strategies based on the seasonal patterns observed in the cryptocurrency market. Our findings also shed light

³At first glance, in the famous painting, *Mona Lisa* seems to be smiling, but at a second glance, her smile fizzles out, and then it appears again but in a different shape. This ambiguous effect is created with the *sfumato* technique, for which Leonardo blurred the contours of *Mona Lisa*’s face.

on the impact of retail traders' weekend and holiday trading on the portfolio performance of institutional traders, albeit to a modest extent. This awareness is crucial for institutional traders as they navigate the dynamics of the market.

All in all, our study emphasizes the need and the importance of incorporating higher-order moments into the modeling process of cryptocurrencies for a more comprehensive understanding of their returns and market dynamics. This would also support policy-makers in understanding risks more accurately and institute closer surveillance of those risks by institutions such as Central Banks.

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Appendix A The reparameterized Johnson's SU distribution

As in Rigby and Stasinopoulos (2005) we consider a reparameterization of the original Johnson Su distribution (Johnson, 1954). For the location and scale parameters $\mu \in \mathbb{R}$ and $\sigma > 0$, respectively, the density evaluated at $x \in \mathbb{R}$ is

$$f(x|\mu, \sigma, \xi, \eta) = \frac{\eta e^{-\frac{1}{2}z^2}}{c\sigma(s^2 + 1)^{\frac{1}{2}}\sqrt{2\pi}}$$

with

$$\begin{aligned} z &= -\xi + \eta \sinh^{-1}(s), \\ s &= \frac{x - \mu + c\sigma w^{\frac{1}{2}} \sinh(\xi/\eta)}{c\sigma}, \\ c &= \left\{ \frac{1}{2}(w - 1) [w \cosh(2\xi/\eta) + 1] \right\}^{-\frac{1}{2}} \end{aligned}$$

and

$$w = e^{1/\eta^2}.$$

The two remaining parameters $\xi \in \mathbb{R}$ and $\eta > 0$ determine skewness and kurtosis, respectively. A positive (negative) value of ξ indicates positive (negative) skewness.