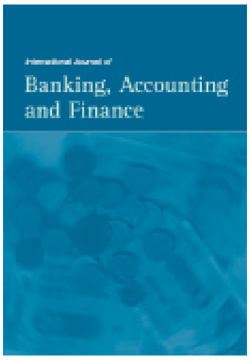

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Is the turn of the month an anomaly on which an investment strategy could be based? Evidence from Bitcoin and Ethereum

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Is the turn of the month an anomaly on which an investment strategy could be based? Evidence from Bitcoin and Ethereum

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Abstract: We examine the turn of the month effect (TOM) in cryptocurrency markets. In contrast to most calendar effect studies, we do not take for granted that the TOM period is the last trading day of the month up to the first three trading days (–1, 3), as Lakonishok and Smidt (1988) proposed in their seminal paper, but we employ an optimisation algorithm which tests several four-day intramonth periods. Our findings confirm the existence of the TOM effect because the most profitable four-day periods are those between the last days of one month and the first trading days of the next one [the (–1, 3) definition is included in these combinations]. We reach the conclusion that the existence of a TOM effect may not always lead to higher profits in comparison with a buy-and-hold (BnH) strategy, but it presents better returns to risk reward and it could be beneficial for investment strategies.

Keywords: turn of the month effect; TOM; calendar anomalies; Bitcoin; Ethereum; pricing efficiency; efficient market hypothesis; EMH; investment strategies.

JEL codes: G10, G14.

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Biographical notes: Evangelos Vasileiou is an Assistant Professor of Finance at the University of the Aegean. His research interests include behavioural finance, financial modelling, financial risk management, and investments analysis. His work has been published in international academic journals such as the *Journal of Behavioural Finance*, the *Journal of Economic Studies*, the *Research in International Business and Finance*, the *International Review of Applied Economics*, the *Computational Economics*, the *Intelligent Systems in Accounting, Finance, and Management*, the *International Journal of Banking, Accounting and Finance*, the *Journal of Financial Regulation and Compliance*, the *Studies in Economics and Finance* and the *Operational Research: an International Journal*, etc.

1 Introduction

Calendar anomalies (CAs) puzzle financial economists and practitioners because CAs question the efficient market hypothesis (EMH) (Fama, 1970) by suggesting that inefficiencies (profit opportunities) arise during specific time periods. Why does CAs question the EMH? According to the EMH, when these anomalies are documented, the financial models should incorporate these inefficiencies into the asset pricing process and eliminate them (Agrawal and Tandon, 1994; Schwert, 2003). However, when profit opportunities persist, the EMH cannot account for these abnormalities. In such cases, scholars propose an alternative approach where abnormalities can be viewed as normal and attributed to a behavioural (usually) reason (Vasileiou, 2018).

Several CAs in capital markets have been documented in the literature. Some of the most examined calendar effects[1] are: the day-of-the-week (French, 1980), the January (Rozeff and Kinney, 1976), the trading month (or fortnight) (Ariel, 1987), the turn of the month (Lakonishok and Smidt, 1988), and the Halloween effect (Bouman and Jacobsen, 2002) amongst others. Many of these anomalies have been examined in cryptocurrencies also: Kaiser (2019), Baur et al. (2019) and Qadan et al. (2021).

In this study, we focus on the turn of the month effect (TOM), which was first documented by Lakonishok and Smidt (1988) and which suggests that the last trading day of each month and the first three trading days of the next month (–1, 3) present on average higher returns than the average returns on the rest of the days of the month. The definition (–1, 3) dominates the TOM studies and is referred to as the TOM period. Following this definition, scholars test the TOM effect in the cryptocurrencies market: Kaiser (2019) tests a wide range of cryptocurrencies and does not find statistically significant evidence for TOM, but in a recent study, Qadan et al. (2021) find statistically significant TOM evidence for BTC. Naeem et al. (2021) test cryptos in a period that includes the COVID-19 outbreak and show that the COVID-19 outbreak adversely affected the efficiency of cryptocurrencies, given a substantial increase in the levels of inefficiency during the COVID-19 period. Fernandes et al. (2022) confirm previous studies that cryptocurrencies exhibit high but slightly varying informational efficiency during both periods.

Depending on the main issue of each study, several approaches have been suggested in order to explain these controversial findings regarding the appearance and disappearance of these anomalies. Connolly (1989) suggests that the contradictory outcomes regarding the existence of CAs could be attributed to inappropriate modelling and the violations of the assumptions of the OLS. Vasileiou (2017) suggests behavioural reasons as to why the TOM effect does not fade, but the optimal TOM window period may have changed over time. Naeem et al (2021) use one-hour data from the cryptocurrency market, and they apply the asymmetric multifractal detrended fluctuation analysis (MF-DFA) in order to measure the asymmetric multifractality which is stronger in the upward trends than in the downward ones.

All the aforementioned studies and the suggested methodologies could be extremely useful depending on the main objective of each study. Our study's scope is to present a behavioural view of the TOM and to suggest an investment strategy that could be applied by anyone. Thus, the suggested method should be relatively simple and easy to understand. In our approach and in contrast to previous TOM studies for cryptocurrencies, we do not take for granted that the TOM period should be (–1, 3), but we employ an optimisation procedure that indicates the most profitable four-day period of the month. This allows us to explore the possibility of the existence of the TOM effect beyond the conventional TOM window period of (–1, 3) and identify patterns of profitability (Vasileiou, 2018).

We test our assumptions using data from 31/12/2017 up to 31/12/2021 for the BitCoin (BTC) and the Ethereum (ETH) cryptocurrencies, which are by far the most highly capitalised and liquid cryptocurrencies.[2] We test both cryptos during whole year time spans in order to isolate our findings from any possible influence of other CAs (Vasileiou, 2017; Qadan et al., 2021). The TOM-based strategy could be an investment suggestion for investors who would like to bear some additional investment risk, but not in such risky assets as the cryptocurrencies, because they increase their risk significantly.

The rest of this paper goes as following: Section 2 describes the data, Section 3 presents the econometric evidence, Section 4 reports the investment strategies returns, and Section 5 concludes the study.

2 Data

We gather daily data for the prices (in USD) from yahoo finance for the period 31/12/2017–31/12/2021 for BTC and ETH. Figure 1 presents the *Price* and the daily returns of BTC and ETH during the examined period. The daily returns are calculated by the formula:

$$Daily\_Returns_t = \frac{Price_t}{Price_{t-1}} - 1 \tag{1}$$

where the $Daily\_Returns_t$ is the return of the cryptocurrency (BTC, ETH) on day *t*, and $Price_t$, $Price_{t-1}$ are the prices of the cryptocurrencies on the day of the calculation and the price of the previous day respectively. Figure 1 shows that volatility is not constant over the tested period, thus, there are indications for volatility clustering for both currencies. Moreover, there are indications of leverage effect because the spikes are longer on both sides (positive/negative returns) when the prices decline.

Table 1 presents the descriptive statistics of the daily returns of our study and the respective histograms. The results show that:

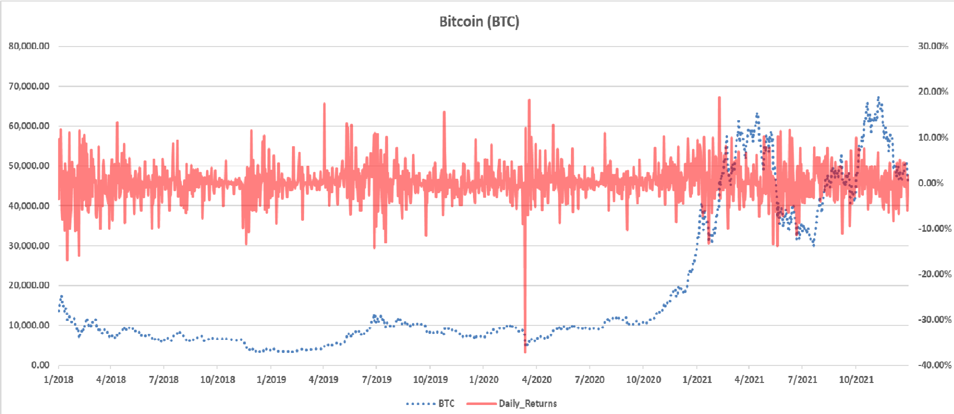
a the times series do not follow the normal distribution, the Shapiro-Wilk test confirms it

b both the daily returns time series are stationary according to the augmented Dickey-Fuller (ADF) test.

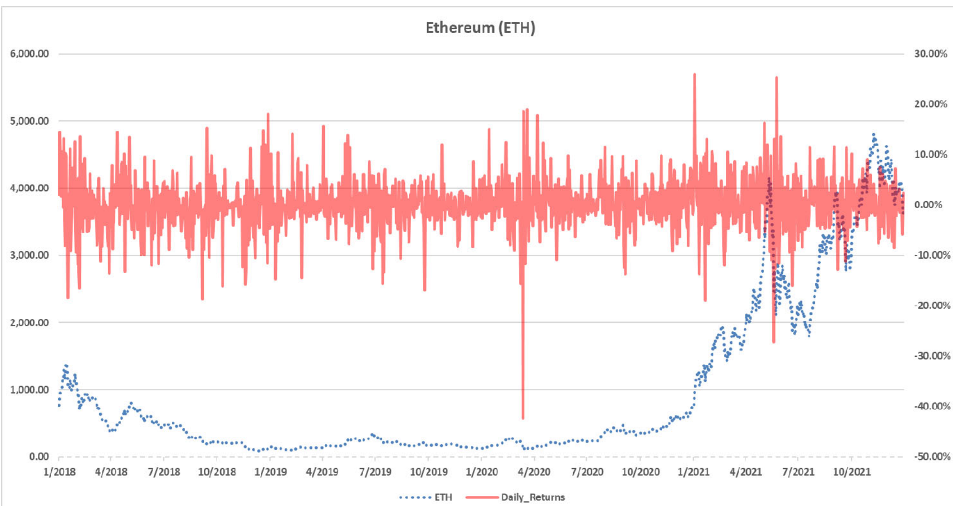
The non-normal distributions of daily returns indicate that a linear model is not appropriate for our dataset, and the stationarity of the time series shows that the daily returns could be used in the model without any further adjustment.

Figure 2 shows the autocorrelation (ACF) of the daily returns to the power of two. The autocorrelation values for each lag are depicted by the spikes. When the spikes are outside the coloured area, there is statistical evidence for autocorrelation and volatility clustering.[3] Therefore, the non-normal distribution and the volatility clustering of the daily returns lead to the conclusion that an OLS model does not fit our dataset and a GARCH family model is more appropriate for our analysis.

Figure 1 Price and daily returns of (a) BTC, (b) ETH (see online version for colours)



(a)

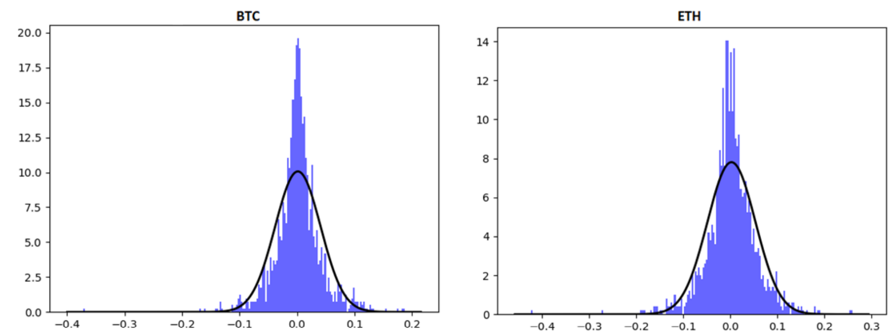


(b)

As far as the optimal TOM period, we initially calculate the average returns and the standard deviation per trading day [as Lakonishok and Smidt (1988) did in their seminal study]. For the cryptocurrencies market, every day is a trading day. Therefore, we examine the range from 12 days before the month change (–12) up to the 15th day (+15) after the month change and the rest of the month days fall under the category 'other days'. Table 2 reports these results. We can observe that there are some intramonth periods that present consecutive positive and high returns. Is the TOM (–1, 3) the best period? Do both currencies have the same optimal period? Is the most profitable intramonth period a period near the turn of the month?

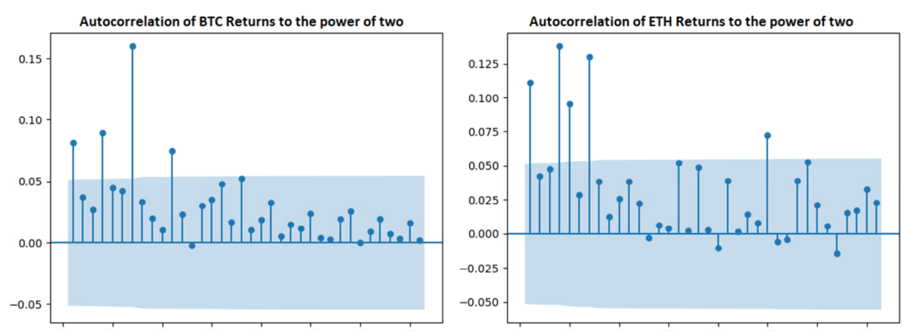
Table 1 Descriptive statistics (see online version for colours)

	BTC	*ETH*
Mean	0.162%	0.243%
Standard deviation	3.963%	5.111%
Minimum	–37.170%	–42.347%
Maximum	18.747%	25.948%
Skewness	–0.422	–0.362
Kurtosis	7.516	5.605
Shapiro-Wilk	0.930*	0.947*
ADF	–26.644*	–11.464*
Observations	1,460	1,460



Notes: *indicates statistical significance at the 1% confidence level.

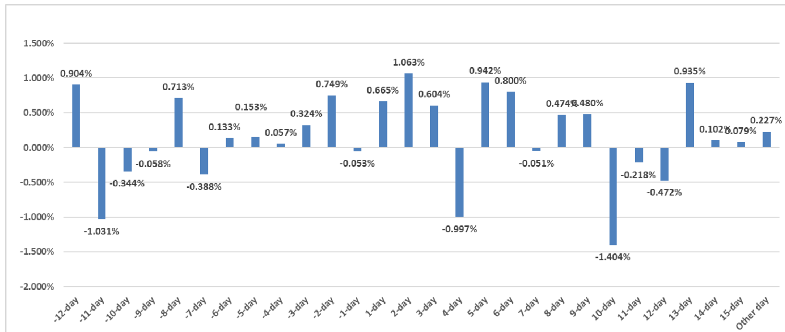
Figure 2 Autocorrelation of the daily returns of the datasets to the power of two: the statistical significance reveals the existence of volatility clustering (see online version for colours)



In order to quantitatively estimate the optimal intramonth period[4], we apply an optimisation procedure which examines all the combinations of the four-day trading periods during the month, and we optimise them according to a chosen criterion. In our study, the chosen criterion is the mean return, following the suggestion by Lakonishok and Smidt (1988). Table 3 reports the average returns, the standard deviation, and the coefficient of variance (CV)[5] of all the tested four-day intramonth subperiods.

Table 2 Descriptive statistics per trading day (see online version for colours)

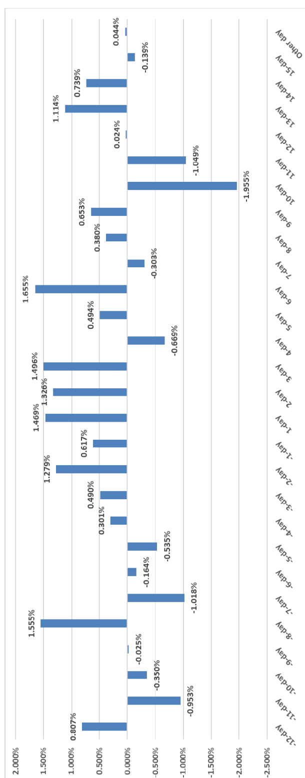
BTC



Trading day	–12-day	–11-day	–10-day	–9-day	–8-day	–7-day	–6-day	–5-day	–4-day	–3-day	–2-day	–1-day	1-day	2-day
Average	*0.904%*	–1.031%	–0.344%	–0.058%	*0.713%*	–0.388%	*0.133%*	*0.153%*	*0.057%*	*0.324%*	*0.749%*	–0.053%	*0.665%*	*1.063%*
St. deviation	*3.984%*	4.481%	3.661%	3.707%	*3.081%*	4.306%	*3.831%*	*4.383%*	*4.035%*	*3.578%*	*3.476%*	3.140%	*3.405%*	*3.947%*
Trading day	3-day	4-day	5-day	6-day	7-day	8-day	9-day	10-day	11-day	12-day	13-day	14-day	15-day	Other days
Average	*0.604%*	–0.997%	*0.942%*	*0.800%*	–0.051%	*0.474%*	*0.480%*	–1.404%	–0.218%	–0.472%	*0.935%*	*0.102%*	*0.079%*	*0.227%*
St. deviation	*3.522%*	3.206%	*4.354%*	*3.394%*	3.546%	*4.499%*	*2.953%*	3.282%	4.054%	6.545%	*4.088%*	*4.125%*	*3.114%*	*4.013%*

Table 2 Descriptive statistics per trading day (continued) (see online version for colours)

ETH



Trading day	−12-day	−11-day	−10-day	−9-day	−8-day	−7-day	−6-day	−5-day	−4-day	−3-day	−2-day	−1-day	1-day	2-day
Average	0.807%	−0.953%	−0.350%	−0.025%	1.555%	−1.018%	−0.164%	−0.535%	0.301%	0.490%	1.279%	0.617%	1.469%	1.326%
St. deviation	5.249%	5.996%	5.082%	4.944%	5.188%	5.004%	4.295%	5.089%	5.841%	4.246%	3.554%	4.045%	4.257%	4.928%
Trading day	3-day	4-day	5-day	6-day	7-day	8-day	9-day	10-day	11-day	12-day	13-day	14-day	15-day	Other day
Average	1.496%	−0.669%	0.494%	1.655%	−0.303%	0.380%	0.653%	−1.955%	−1.049%	0.024%	1.114%	0.739%	−0.139%	0.044%
St. deviation	6.248%	3.858%	5.305%	4.848%	4.345%	5.152%	3.381%	4.339%	4.943%	7.534%	5.662%	5.880%	4.165%	5.159%

Table 3 Optimal intra-month four-day trading periods: ranking based on the average return criterion

BTC				
Combination	*Observations*	*Average returns*	*Standard deviation*	*CV*
TOM(–2, 2)	191	0.609%	3.539%	0.172
TOM(–1, 3)	191	0.573%	3.549%	0.161
(5, 8)	192	0.541%	4.006%	0.135
TOM(–3, 1)	191	0.424%	3.429%	0.124
(6, 9)	192	0.426%	3.664%	0.116
(2, 5)	192	0.403%	3.881%	0.104
(1, 4)	192	0.334%	3.627%	0.092
(3, 6)	192	0.337%	3.737%	0.090
(–5, –2)	192	0.321%	3.905%	0.082
(–4, –1)	191	0.271%	3.597%	0.075
(4, 7)	192	0.173%	3.742%	0.046
(–6, –3)	192	0.167%	3.979%	0.042
(–8, –5)	192	0.153%	3.964%	0.039
(12, 15)	192	0.161%	4.683%	0.034
(–9, –6)	192	0.100%	3.788%	0.026
(11, 14)	192	0.087%	4.863%	0.018
(–10, –7)	192	–0.019%	3.750%	–0.005
(–7, –4)	192	–0.011%	4.161%	–0.003
(7, 10)	192	–0.125%	3.707%	–0.034
(–12, –9)	192	–0.132%	4.043%	–0.033
(8, 11)	192	–0.167%	3.835%	–0.044
(–11, –8)	192	–0.180%	3.827%	–0.047
(10, 13)	192	–0.290%	4.743%	–0.061
(9, 12)	192	–0.403%	4.500%	–0.090
ETH				
Combination	*Observations*	*Average returns*	*Standard deviation*	*CV*
TOM(–1, 3)	191	1.230%	4.975%	0.247
TOM(–2, 2)	191	1.175%	4.250%	0.277
TOM(–3, 1)	191	0.965%	4.068%	0.237
(1, 4)	192	0.905%	5.004%	0.181
(3, 6)	192	0.744%	5.235%	0.142
(–4, –1)	191	0.672%	4.533%	0.148
(2, 5)	192	0.661%	5.241%	0.126
(6, 9)	192	0.596%	4.549%	0.131
(5, 8)	192	0.556%	4.989%	0.112
(–5, –2)	192	0.384%	4.817%	0.080

Table 3 Optimal intra-month four-day trading periods: ranking based on the average return criterion (continued)

		ETH		
Combination	*Observations*	*Average returns*	*Standard deviation*	*CV*
(12, 15)	192	0.435%	5.969%	0.073
(4, 7)	192	0.294%	4.719%	0.062
(11, 14)	192	0.207%	6.151%	0.034
(–9, –6)	192	0.087%	4.970%	0.017
(–11, –8)	192	0.057%	5.412%	0.010
(–10, –7)	192	0.040%	5.156%	0.008
(–6, –3)	192	0.023%	4.941%	0.005
(–8, –5)	192	–0.041%	5.014%	–0.008
(–12, –9)	192	–0.130%	5.385%	–0.024
(7, 10)	192	–0.306%	4.478%	–0.068
(–7, –4)	192	–0.354%	5.123%	–0.069
(8, 11)	192	–0.493%	4.642%	–0.106
(10, 13)	192	–0.467%	5.876%	–0.079
(9, 12)	192	–0.582%	5.386%	–0.108

Using the higher average returns as a criterion, the findings show that for BTC the best period for investment is the period from the last two trading days of the month up to the first two trading days of the next month (–2, 2), which is a TOM period, but not the dominant (–1, 3) definition. Our findings show that the (–1, 3) period ranks second in terms of profitability in the BTC market. For ETH, the optimal period is the dominant (–1, 3) subperiod if we consider the returns as criterion, but if we optimise the procedure with the CV as criterion the optimal period is the (–2, 2). Thus, if the CV was the optimisation criterion, then the optimal period for both currencies would be the (–2, 2) period.

However, we should highlight that no matter which criterion between average return and CV will be applied, from the results of Table 3, the most profitable intramonth days for investment belong to periods near the TOM: the three TOM combinations (–3, 1), (–2, 2), and (–1, 3) are amongst the most profitable combinations for both currencies. These findings confirm that there is a TOM CA, because days near the TOM present the higher returns on average.

3 Econometric modelling

As we present in Section 2, a GARCH family model is more appropriate for our dataset than an OLS model due to the non-normal distribution of the time series and the volatility clustering. We tested several GARCH models and the Akaike and Schwarz information criteria showed that the exponential GARCH (EGARCH), which was initially suggested by Nelson (1991), is the most appropriate. We employ the mean equation:

$$Daily\_Returns_t = c + b_1 \times TOM_t + \varepsilon_t \tag{2}$$

where $Daily\_Returns_t$ is the return on day t, c is the intercept and represents the average returns, and b_1 is a TOM coefficient which shows the outperformance of TOM days relative to the rest of the month days. TOM_t is a dummy variable that takes value 1 if it belongs to the TOM (–2, 2) intramonth period for the BTC and to the (–1, 3) for the ETH case, and 0 otherwise, while ε_t is the error term that follows the normal distribution with mean zero and standard deviation σ_t. If $b_1 > 0$ and statistically significant, there is evidence for TOM effect.

The conditional variance for the EGARCH(1, 1, 1) model is

$$\log\left(\sigma_t^2\right) = \alpha_0 + \alpha_1 \times \left|\frac{\varepsilon_{t-1}}{\sigma_{t-1}}\right| + \beta_1 \times \log\left(\sigma_{t-1}^2\right) + \gamma_{EGARCH} \times \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \quad (3)$$

where the modelling of the variance equation with the log guarantees the non-negativity of the σ_t^2 even when the parameters are negative. α_1 and β_1 are the ARCH and GARCH coefficients respectively, and γ_{EGARCH} is the term of the leverage effect (when $\gamma_{EGARCH} <$ 0).

Table 4 Results of EGARCH(1, 1) in-sample estimations

EGARCH (1, 1, 1) estimation		
Mean equation		
	BTC	*ETH*
c	0.000880	0.001243
	(0.001081)	(0.001365)
TOM	0.005261	0.009727*
	(0.002619)**	(0.003306)
Conditional variance		
α_0	–0.519100*	–0.471263*
	(0.077323)	(0.074484)
α_1	0.138083*	0.150924*
	(0.019185)	(0.018001)
β_1	0.935291*	0.939827*
	(0.010120)	(0.011037)
γ_{EGARCH}	–0.045389*	–0.025580*
	(0.007580)	(0.008461)
Q-statistics and ARCH LM tests		
Q_1	0.1188	0.9253
Q_2	2.2603	5.5794
Q_3	2.6780	6.6208
Q_4	4.1518	7.6565
Q_5	6.4414	8.7695
LM_1	0.002597	0.002997
LM_2	0.059903	0.304082

Notes: * and ** indicate statistical significance at the 1% and 5% levels respectively. The LM tests are measured by the observations multiplied by the R-squared. We present the standard errors in parentheses.

Table 4 reports the quantitative results of our model, which show that in both cases there is strong statistical evidence pointing to the existence of a TOM effect, because b_1 is positive and statistically significant in both cases. Moreover, there is leverage effect because the γ_{EGARCH} coefficient is negative and statistically significant, which means that the asymmetric modelling is appropriate for our dataset. The Q and LM test the econometric validity and show that our models do not suffer from autocorrelation and ARCH issues.

4 Investment strategies based on the TOM effect and EMH

The empirical evidence is in favour of the existence of the TOM effect, which is an indication of an EMH violation because there are profit opportunities in specific time periods. We examine if a strategy based on the aforementioned findings outperforms the buy-and-hold (BnH) strategy. We assume that during the TOM days, we convert our investment amount to BTC and ETH, and during the rest of the month days we convert them to USD and we deposit them in a zero-rate deposit account.

In order to apply TOM-strategies to our sample, we should make 96 transactions. Thus, each investor-scholar should take these costs into consideration in his/her final results. The transactions for the BnH strategy are only two, so the transaction costs for the BnH are significantly lower than those for the TOM-based strategies. We do not include transaction costs in our calculations because it depends on the invested amount and the transaction cost of each platform.

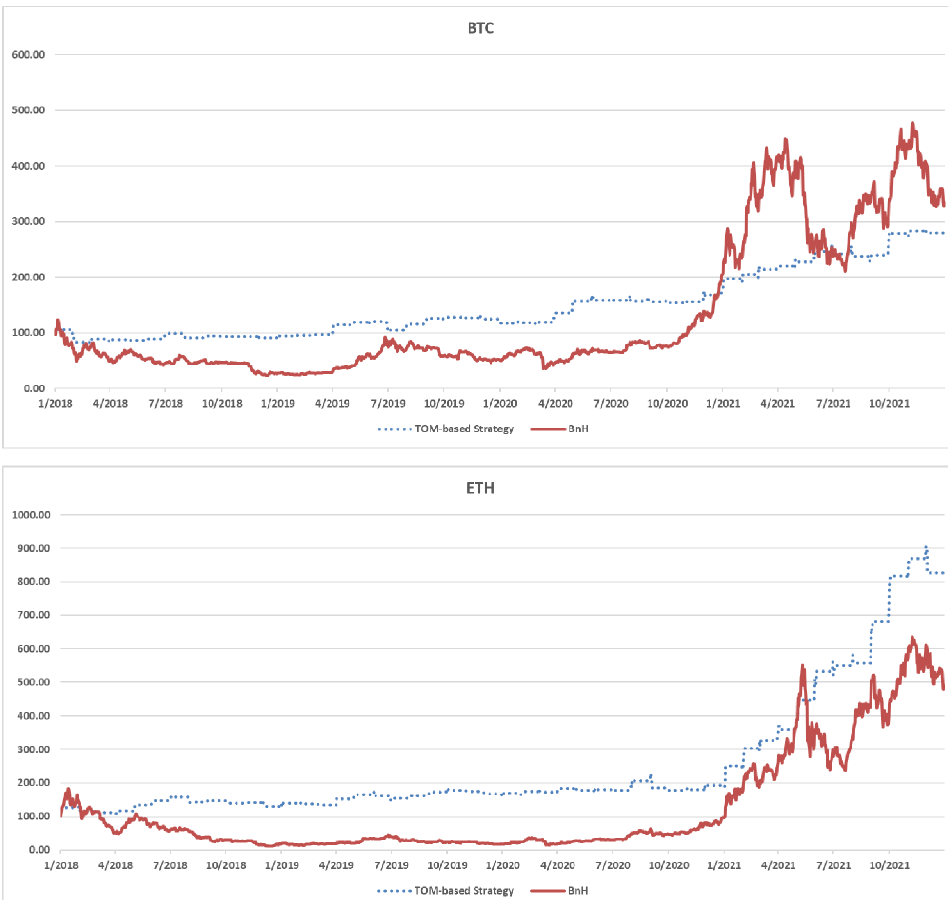
The comparisons of these strategies are reported in Table 5 and show that for the BTC case the BnH strategy outperforms the TOM(–2, 2) strategy, but the latter has significantly lower risk (standard deviation) considering the investment in BTC takes place only for 191 days out of the 1,460 of the sample. However, if we consider the transaction costs, the benefits of a TOM-based strategy are significantly reduced for the BTC case because a significant number of profits run from the investors to the traders (Vasileiou, 2015). The TOM based investment plan may offer an advantage in terms of risk considering the shorter investment period, but this becomes a drawback in terms of the profits when there is only a long-term growth period (Vasileiou, 2017).

As far as ETH is concerned, the TOM based strategy is significantly more profitable than the BnH (725.95% vs. 390.77%) and bears significantly lower risk. In this case, we can assume that the TOM strategy outperforms the BnH strategy even when the transaction costs are included in the estimations because the TOM strategy returns are achieved with significantly lower risk and this offsets any advantages of the BnH even in a hypothetical scenario where the transaction costs reduce TOM (–1, 3) strategy profits to equal those of the BnH.

Figure 3 presents the performance of these strategies during the sample period. We can observe that when there are no periods of long-term skyrocketing price increases, the TOM-strategies outperform the BnH, even in the BTC market. This is logical because a TOM-based strategy gets profits only for four days per month, but the BnH can get profits for more days (during the non-TOM days as well). One way to outperform the

BnH strategy would be to make an investment with a leveraged position during the TOM days, which means that the risk increases, and this way we may outperform the BnH strategy due to the increased mean average returns during the specific trading days (Vasileiou, 2021). However, even with no leverage the TOM strategies outperform the BnHs in terms of returns per unit of risk (risk reward ratios). As Table 5 shows, the CV of the TOM strategies is significantly lower than the respective CV of the BnH strategies, which means that it could be suggested as a balanced investment strategy for modestly risk-loving investors.

Figure 3 TOM-based strategies versus BnH (see online version for colours)



Notes: We examine if a strategy based on the aforementioned findings outperforms the BnH strategy. We assume that during the TOM days we convert our investment amount to BTC and ETH, and during the rest of the month days we convert them to USD and we deposit them in a zero-rate deposit account.

Table 5 Comparison of TOM-based strategies and BnH

Strategy	*Cumulative returns*	*Investment days*	*Annualised standard deviation*	*CV*
		BTC		
BnH strategy	233.26%	1,460	75.709%	3.081
TOM(–2, 2) strategy	184.14%	191	24.711%	7.452
		ETH		
BnH strategy	390.77%	1,460	97.654%	4.002
TOM(–1, 3) strategy	725.95%	191	35.191%	20.629

Notes: The BnH strategy assumes that we buy the crypto (BTC/ETH) at the beginning of the examined period and we calculate the returns at the end of the period. As far as the TOM strategy, we assume that during the TOM days we convert our investment amount to BTC and ETH, and during the rest of the month days we convert them to USD and we deposit them in a zero-rate deposit account. The results show that a TOM based strategy outperforms the BnH only in the case of ETH, when there is no leverage and the criterion is the cumulative returns. This is logical because a TOM-based strategy gets profits only for four days per month, but the BnH can get profits for more days (during the non-TOM days as well). One way to outperform the BnH strategy would be to make an investment with a leveraged position during the TOM days (Vasileiou, 2021). However, even with no leverage the TOM strategies outperform the BnHs in terms of returns per unit of risk. As Table 5 shows, the CV of the TOM strategies is significantly lower than the respective CV of the BnH strategies, which means that it could be suggested as balanced investment strategy for modestly risk-loving investors.
Annualised standard deviation = daily standards deviation x sqrt(365).
CV is the ratio of average returns to the standard deviation and shows the compensation per unit of risk, thus, the higher CV, the better.

5 Conclusions

The aim of this study was twofold:

a to test the intramonth CAs, and especially the TOM effect, in the cryptocurrency market

b to explore whether a strategy based on our TOM findings could be beneficial for an investor.

The empirical findings confirm that BTC and ETH markets present inefficiencies as far as the existence of the TOM effect. The optimisation algorithm we developed shows that the most profitable four-day intramonth investment periods are those near the end of each month and the beginning of the next one. Several explanations could be suggested for this seasonality, such as the ‘payment hypothesis’ (McConnell and Xu, 2008). The TOM effect persists; however, the optimal period is not always the dominant (–1, 3) TOM definition.

Does the existence of the TOM effect suggest a violation of the EMH? For the ETH case, the findings show that there is a violation of the EMH because a TOM-based strategy not only outperforms the BnH strategy, but also bears lower risk. However, for the BTC case we cannot draw similar conclusions unless we take some additional risk and take a leveraged position during the investment days. Nonetheless, in both cryptos the returns to risk ratio (CV) shows that the TOM-based investment strategy outperforms the BnH, which means that the TOM-based strategy could be an investment strategy for investors who would like to bear investment risk, but not in such risky assets as the cryptocurrencies.

Further research in this direction should be carried out examining not only additional cryptocurrencies, but also other asset classes, e.g., stocks, bonds, or utility tokens, and the practical implications of TOM-based leveraged strategies.

As far as the methodology is concerned, the next step in exploring this optimisation procedure could be to examine longer than four-day periods in order to draw conclusions as to whether an intramonth investment strategy could outperform the BnH strategy. The four-day investment period may be too short for this, e.g., in the BTC case, could a 5-or 6-day period be more appropriate for this strategy? Moreover, even if the four-day strategy is adopted, which is the appropriate ratio of leverage that could lead to increased profits without increasing the risk significantly? Could asymmetry models such as the MF-DFA be useful in this strategy and suggest different leverage ratios depending on the trends (upwards/downwards)? The suggestions in this paper and the aforementioned scientific questions for further research should not be limited to the cryptocurrency market, but the scope should expand to include other assets, e.g., stocks, bonds, FX.

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Notes

1 The terms calendar effects and CAs are used interchangeably.

2 Moreover, we choose these cryptocurrencies because they have constantly been the most highly capitalised cryptos in the last years and are ranked in the 1st and 2nd place according to this classification. Investors' interest in other cryptos, as this interest is expressed by the capitalisation, is time varying and for some periods a crypto is the third most capitalised while in another period the same crypto ranks lower (source for the capitalisation of the cryptos: https://coinmarketcap.com).

3 This is an additional indication that linear models are not appropriate for our sample.

4 We refer to intramonth periods because the optimisation procedure may show that the optimal period is one of (–3, 1), (–2, 2), (–1, 3) which are TOM periods. However, the optimisation procedure may suggest a period that does not belong to a TOM span, e.g., (–4, –1), (3, 6). Thus, we do not assume that the optimal period is the Lakonishok and Smidt (1988) TOM (–1, –3), but we rely on the algorithm to show us the best period for investment.

5 CV is the ratio of average returns to the standard deviation and shows the compensation per unit of risk, thus, the higher CV, the better.