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A new perspective of the day-of-the-week effect on Bitcoin returns: evidence from an event study hourly approach

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Abstract

Research background: A current strand of the financial literature is focusing on detecting inefficiencies, such as the day-of-the-week effect, in the cryptocurrency market. However, these studies are not considering that there are no daily closes in this market, and it is possible to trade cryptocurrencies on a continuous basis. This fact may have led to biases in previous empirical results.

Purpose of the article: We propose to analyse the day-of-the-week effect on the Bitcoin from an alternative perspective where each hourly data in a day is considered an event. Focusing on that objective, we employ hourly closing prices for Bitcoin which are taken from the Kraken exchange, one of the world leading exchanges and trading platforms in the cryptocurrency markets, for the period spanning from January 2016 to December 2021.

Methods: Contrary to the previous empirical evidence, we do not calculate daily returns, but rather the first stage of our proposed approach is devoted to analysing the hourly mean returns for each of the 24 hours of the day for each day of the week. We look for statistically significant hourly mean returns that could advance the importance of the hourly differentiation in the Bitcoin market. In a second stage, we calculate different post-event cumulative returns which are defined

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as the change in log prices over a time interval. Finally, we propose different investment strategies simply based on the significant hourly mean returns we obtain and we evaluate their performance in terms of the Sharpe ratio.

Findings & value added: We contribute to the debate about the degree of Bitcoin's market efficiency by providing an alternative methodology based on an event study hourly approach. Furthermore, we provide evidence that by investing in different post-event hourly windows it is possible to outperform the classic buy-and-hold strategy.

Introduction

There is a principle in finance called Efficient Market Hypothesis (EMH hereafter) that has its roots in the 1960s, when Fama (1965) and Samuelson (1965) considered the capital markets to be efficient. That means that stock prices reflect all available information, that there is no possibility of finding patterns in price, and that price changes in one period are independent of changes in the previous one.

Roberts (1967) distinguished three levels of efficiency based on the degree of information reflected in stock prices. The first one is the weak-form hypothesis, which asserts that stock prices reflect all information derived by past prices, trading volume or short interest. This form implies that trend analysis is fruitless. The second hypothesis is the semi-strong form, which states that a market is efficient if all relevant publicly available information is reflected in the market price. The third hypothesis is named strong-form, and states that market prices should reflect all information (public or not) that is relevant to the value of the asset. Therefore, according to these hypotheses, prices would follow a random walk and there would be no detectable patterns.

However, this principle has generated a great deal of controversy and there is vast empirical evidence against market efficiency which has shown different anomalies that investors could exploit (technical trading rules that are profitable, the superior performance of small firms, returns that appear to be higher in January than in other months or significant differences in returns on different days of the week are just some of these anomalies).

New financial assets, such as cryptocurrencies, are not free of this controversy, see Merediz-Solà and Bariviera (2019), Kyriazis (2019) and Bariviera and Merediz-Solà (2021). The first evidence that Bitcoin is not weakly efficient was provided by Urquhart (2016), who also stated that this asset shows a tendency to become more efficient. The existence of predictable patterns and different inefficiencies in the cryptocurrency markets were later corroborated by Phillip *et al.* (2018) and Vidal-Tomás *et al.* (2019), among others.

Different inefficiencies or anomalies have been defined, such as overreactions, calendar effects, fat tails or size effects that have been analysed from several points of view and using different databases including cryptocurrencies, see De Bondt and Thaler (1985, 1987), Atkins and Dyl (1990), Bremer and Sweeney (1991), Caporale *et al.* (2016), Zhang *et al.* (2017), Aharon and Qadan (2019), Caporale and Plastun (2019), Kaiser (2019), Ma and Tanizaki (2019), Miwa (2019), Qadan *et al.* (2019), Bogards and Czudaj (2020), Qadan and Idilbi-Bayaa (2021) and Chiah and Zhong (2021), among others.

In this context, there is a stream of the empirical literature, the so-called event studies, which focuses on the short-term stock price reaction to different shocks or announcements. Based on this strand of the literature, we provide an alternative perspective to the debate about the degree of market efficiency of cryptocurrencies and improve the previous empirical evidence in various ways.

Firstly, we use a standard event study methodology for the purpose of analysing the day-of-the-week effect from an alternative point of view that, to the best of our knowledge, has not been employed previously for cryptocurrency or other assets. We adapt the approach proposed by Fung *et al.* (2000) and Grant *et al.* (2005), who analyse market behaviour after different events by considering each hour of each trading day as an event day. Therefore, we study whether Bitcoin hourly returns are statistically significant, but also different post-event hourly windows. The main reason for focusing on Bitcoin is the increasing importance of crypto assets, and especially Bitcoin, in the new economy, where they have become a financial asset to be considered. We focus on the Bitcoin because this cryptocurrency is the best-known one and also the first one on which derivatives and other financial assets such as Exchange Traded Funds (ETFs) have been created and traded. In that context, it is important to know its behavioural patterns and whether there is the possibility of making a profit from this calendar anomaly.

Secondly, Doyle and Chen (2009) show that the day-of-the-week effect is very sensitive to the choice of the subperiods. For that reason, but also as a kind of robustness test, we apply our proposed methodology to several samples using a rolling window approach. Finally, we suggest a trading strategy based on the main results and we test its performance by calculating the Sharpe ratio.

Our initial results show in the first instance that there are not many hours in different days of the week in which there are significant average returns. However, once the focus is over the subsequent post-event hours and their average cumulative returns, we observe significant positive val-

ues, especially on Mondays, Fridays and Sundays. Nevertheless, additional robustness tests indicate that, in fact, the returns that are most consistent over time in terms of significance are those on Fridays at 3 p.m. Finally, it is proven that holding investments in Bitcoins for some hours after Fridays at 3 p.m. yield better performances than other options which make them a good choice for investors.

The rest of the paper is organized as follows. Section 2 describes the previous empirical evidence. Section 3 defines the theoretical background for this paper. Section 4 reports the empirical results of the study. Section 5 provides the robustness test results. Lastly, Section 6 sets out the main conclusions.

Literature review

There are different assumptions in a perfect market, but one of the most important ones is that prices would instantaneously reflect all available and relevant information. Fama (1965, 1970) stated that a stock price reflects all available information in the market and that anyone who beats it would be doing it by sheer luck. However, there are a vast number of papers that have been published documenting the inefficiency of the markets and the presence of the so-called market anomalies that can be exploited through appropriate trading strategies.

One of the ways of proving the existence of market inefficiencies are the so-called “event studies”, where the post-event return performances of assets are tracked for a period following the events. They were introduced by Ball and Brown (1968) and Fama *et al.* (1969), but also by Brown and Warner (1985), Dodd and Warner (1983) and MacKinlay (1997), who explain a methodology that is still employed nowadays by using the largest variety of economic events, especially the market reaction after positive and negative shocks. We find studies which show that shifts in prices are followed by price movements in the opposite direction (overreaction effect) such as those of De Bondt and Thaler (1985, 1987), Atkins and Dyl (1990), Bremer and Sweeney (1991), Dissanaikie (1994), Gunaratne and Yonesawa (1997), Fung *et al.* (2000), Benou and Richie (2003), Grant *et al.* (2005), Ising *et al.* (2006), Miralles-Marcelo *et al.* (2010, 2014), Choi and Hui (2014), Lalwani *et al.* (2019), Miwa (2019), and Bogards and Czudaj (2020), among others. On the other hand, we also find studies which report that these shifts lead to price movements in the same direction which is known as the momentum effect or underreaction, see Jegadeesh and Titman (1993), Cox and Peterson (1994), Lasfer *et al.* (2003), Savor (2012),

Caporale and Plastun (2019), Kosc *et al.* (2019), and Qing *et al.* (2019), among others.

Seasonal or calendar anomalies (January effect, December effect, weekend effect or day-of-the-week effect), where statistically significant returns are found for different months or days, have also been identified by several authors using numerous procedures, assets and data samples. The works of Cross (1973), Rozeff and Kinney (1976), Gultekin and Gultekin (1983), Lakonishok and Smidt (1988), Sias and Starks (1995), Choudhry (2001), Cai *et al.* (2006), and more recently Caporale *et al.* (2016), Zhang *et al.* (2017), Qadan *et al.* (2019), Qadan and Idilbi-Bayaa (2021) and Chiah and Zhong (2021) are just a few examples of the vast empirical evidence in this strand of the literature.

Efficiency of new financial assets such as cryptocurrencies has been also tested from different points of view, see Corbet *et al.* (2019) and Jalal *et al.* (2022), for a systematic review of the empirical literature, where different event day analysis and calendar anomalies are also considered.

Caporale and Plastun (2019) confirm the existence of price patterns after overreactions and suggest that next-day price changes in both directions are greater than after normal days, although they also state that a trading strategy based on these results is not profitable. In contrast, Panagiotis *et al.* (2019), Tzouvanas *et al.* (2020) and Yukun and Tsyvinski (2021) find strong momentum effects in the cryptocurrency market. These results are consistent with those by Caporale and Plastun (2020), who examine the existence of a momentum effect after one-day abnormal returns and find evidence that hourly returns during the day of positive (negative) abnormal returns are higher (lower) than on normal days. In this case, they find some price patterns that can form the basis for a profitable trading strategy.

Bogards and Czudaj (2020) examine the prevalence of price overreaction for different cryptocurrencies compared to the U.S. stock market and find evidence of a high prevalence of overreaction, as did Zaremba *et al.* (2021), who also found a reversal effect where cryptocurrencies with low returns on the previous day outperform those with high returns.

Relative to the day-of-the-week effect, Dorfleitner and Lung (2018) model daily differences in the return and volatility of cryptocurrencies with an EGARCH model using daily data from 8 August 2015 to 7 August 2018. They observe that returns of all cryptocurrencies considered on Sundays were significantly lower than those on other days. Aharon and Qadan (2019) use OLS and GARCH models with daily data from 2010 to 2017 and provide evidence of the existence of the day-of-the-week effect on Bitcoin. More precisely, they show that Mondays are associated with higher returns and volatility. Caporale and Plastun (2019) also focus on the day-

of-the-week effect and apply different parametric and non-parametric methods (average analysis, Student's test, ANOVA, the Kruskal-Wallis and Mann-Whitney test, and regression analysis with dummy variables). Once the previous models have been applied to daily data spanning from 2013 to 2017, they merely provide evidence of higher returns on Mondays than those on the other days of the week for the Bitcoin.

Kaiser (2019) tests for the existence of seasonality patterns with respect to various cryptocurrency returns and another three metrics and finds that the day-of-the-week effect only occurs for Bitcoin. More recently, Qadan *et al.* (2022) analysed a set of seasonal patterns of different cryptocurrencies using various OLS models and daily data from July 2016 to January 2020. Focusing exclusively on their results related to the day-of-the-week effect, they only found statistically significant cases in Bitcoin and Nem and observed that Monday returns are linked to a positive tendency for positive returns.

To sum up, previous empirical evidence has focused on analysing different asset patterns using the most various methodologies. However, Bitcoin's market trades 24 hours a day 7 days a week and there is a lack of evidence focusing on analysing that circumstance that it is proposed to be filled with this research.

Research methods

The notion of informationally efficient markets leads us to consider that crypto prices reflect all available information. Therefore, accordingly with the EMH, not statistically significant positive or negative returns should occur with the arrival of new information.

One of the main characteristics of the cryptocurrency markets is that they never sleep because they trade twenty-four hours a day seven days a week and, consequently, there are no closing times. However, most of the previous empirical evidence states that they used daily prices without specifying the hourly reference taken to calculate the daily return (only Dorfleitner and Lung, 2018, point out that they employ daily data of cryptocurrencies at 12 a.m. coordinated universal time). From our point of view, this is a fact that can bias the results of empirical evidence and, therefore, it must be considered.

We propose to analyse the day-of-the-week effect on the Bitcoin from an alternative perspective, where each hourly data in a day is considered an event. To achieve that objective, we employ an event study procedure which is in line with that proposed by Fung *et al.* (2000), Grant *et al.*

(2005) and Miralles-Marcelo *et al.* (2014), among others, but which, to the best of our knowledge, has not been previously employed in the cryptocurrency market.

Focusing on that objective, we employ hourly closing prices for Bitcoin which are taken from the Kraken exchange (www.kraken.com) — one of the world leading exchanges and trading platforms in the cryptocurrency markets — for the period spanning from 1 January 2016 to 31 December 2021 (which amounts to 52,608 hourly observations). Eastern Standard Time (EST) is the standard time zone used in this paper.

Contrary to the previous empirical evidence, we do not calculate daily returns, but rather the first stage of our proposed approach is devoted to analysing the hourly mean returns for each of the 24 hours of the day for each day of the week. We look for statistically significant hourly mean returns that could advance the importance of the hourly differentiation in the Bitcoin market. As an example, if we take 12 p.m. as the reference of the event time, which will be always denoted as 0, the initial return will be calculated considering the prices that cover the period between 12:00 p.m. and 12:59:59 p.m.

In a second stage, we calculate different post-event cumulative returns (CR_t) which are defined as the change in log prices over a time interval.

$$CR_t = \ln\left(\frac{P_t}{P_0}\right) \quad (1)$$

Where P_t and P_0 are the Bitcoin closing prices on each hour following the event and the price at the event time, respectively. We have considered nine different post-event hourly intervals following the event to calculate cumulative returns: 1 (following the previous example, prices between 13:00 p.m. and 13:59:59 p.m. are considered), 2 (13 p.m. to 14:59:59 p.m.), 3 (13 p.m. to 15:59:59 p.m.), 4 (13 p.m. to 16:59:59 p.m.), 5 (13 p.m. to 17:59:59 p.m.), 6 (13 p.m. to 18:59:59 p.m.), 12 (13 p.m. to 12:59:59 a.m.), 18 (13 p.m. to 06:59:59 a.m.) and 24 (13 p.m. to 12:59:59 p.m. of the following day). These cumulative returns are averaged to obtain the average cumulative return as follows:

$$ACR = \frac{I}{N} \sum_{t=1}^N CR_t \quad (2)$$

where N is the number of events corresponding to each filter. A traditional t -test is calculated to check whether these average cumulative returns are significantly different from zero. The t -statistic is obtained as:

$$t = \frac{ACR}{\sigma / \sqrt{N}} \quad (3)$$

Where σ is the standard deviation of the cumulative returns and N is the number of shocks. A statistically significant value for an ACR would be consistent with the existence of a day-of-the-week effect. It is worth highlighting that, following Caporale and Plastun (2020), the average cumulative returns do not incorporate transaction costs because these costs in internet trading are negligible and excluding them does not affect the results.

Figure 1 sets out the Bitcoin's hourly closing prices in American dollars (Y-Axis) for the period which spans from 1 January 2016 to 31 December 2021 (X-axis). Bitcoin's prices are characterised by sharp upward and downward trends in 2018, 2020 and 2021, which are mixed with the theoretically calm periods of 2016, 2017 and 2019, where the prices followed a sideways trend. Summary statistics for the hourly price return series are reported in Table 1.

We observe that higher positive returns are obtained for Fridays and Sundays, while the most negative ones are yielded on Thursdays and Saturdays. However, based on the ANOVA test, we cannot reject the null hypothesis that all the days have the same mean since these differences are not statistically significant. The skewness statistics indicate mixed positive and negative biases while the kurtosis statistics show that all days have a leptokurtic distribution.

Results

The initial results of our procedure are shown in Table 2, reporting mean returns and t -statistics (in parentheses) for each hour and day. Some conclusions can be drawn from these preliminary results. Firstly, there are eleven hours where none of the coefficients are statistically significant and seven more where just one of the coefficients is significant. This means that there are just six hours in the day (7 a.m., 12 p.m., 4 p.m., 5 p.m., 6 p.m. and 7 p.m.) where we can find two or more statistically significant coefficients over the seven days of the week. Focusing just on the significant values, we find positive significant mean returns on Mondays and Fridays

at 7 a.m. but negative on Sundays, negative significant mean returns on Mondays and Fridays at 12 p.m. and mostly positive mean returns, except on Tuesdays and Wednesdays, for the time slots that spans from 4 p.m. to 7 p.m.

It also worth pointing out that we find isolated significant negative mean returns at night, from 8 p.m. to 11 p.m., on Wednesdays, Thursdays, and Saturdays.

The fact that only 21 out of 168 coefficients appear to be statistically significant led us to initially agree with the strand of the empirical evidence which states that there is not a day-of-the-week effect on the Bitcoin. However, it also led us to ask ourselves what would happen if instead of analysing only those returns we also analysed the post hourly behaviour of the Bitcoin price.

Tables 3 to 9 report the average cumulative returns 1, 2, 3, 4, 5, 6, 12, 18 and 24 hours following the hourly event of each day, as well as their respective t-stats (in parentheses). The results of Monday's post-event holdings for each hour, which are shown in Table 3, reveal how important is to focus not only on the event, but also on the following returns. We find that mean returns at 7, 12 and 16 hours that were significant when only the event hour is considered are not followed by any statistically significant coefficients on the post-event hours, while just the average cumulative return 1 hour after the event at 17 hours is significant. On the other hand, we find two time slots that were not considered in the initial estimation, from 4 a.m. to 6 a.m. and from 12 p.m. to 3 p.m., where we find positive and significant coefficients which increase as the post-event number of hours considered increases.

The low significance of Bitcoin movements at almost any time of the day on Tuesdays, Wednesdays and Thursdays is confirmed in the results of Tables 4 to 6, where just a few coefficients are statistically significant on Tuesday (Table 4) from 9 p.m. onwards and on Thursdays (Table 6) from 5 p.m. onwards.

In contrast, Fridays are revealed as the most important days in Bitcoin trading in view of the results shown in Table 7. Once again, the longer the time considered for calculating the cumulative returns, the higher the averages obtained in all cases. We find that most of the average cumulative returns 18 and 24 hours after each event are positive and statistically significant. The results also show that the average cumulative returns following trades from 12 a.m. to 2 a.m. are mostly significant, as well as most of those from 3 p.m. to 6 p.m., especially those obtained at 4 p.m., where all of them are significant.

Finally, the results reported in Tables 8 and 9, which correspond to the weekend trades on Saturdays and Sundays respectively, reveal a divergent behaviour on both days. We find only a few of significant average cumulative returns on Saturdays. They are concentrated over 5 p.m. onwards and most of them are negative. On the other hand, there are far more statistically significant average cumulative returns on Sundays, especially from 9 a.m. to 3 p.m., most of them positive.

Discussion

The efficiency or not of cryptocurrencies is a topic that lacks a conclusive result. Nadarajah and Chu (2017) highlighted the efficiency of Bitcoin employing daily returns. Vidal-Tomás and Ibáñez (2018) observe that Bitcoin becomes more efficient over time in relation to its own events and López-Martín *et al.* (2021) also stated that Bitcoin increases its efficiency over time. On the other hand, Kurihara and Fukushima (2017) find that the Bitcoin market is not efficient, which is the same conclusion as the one drawn by Bariviera (2017), who shows that Bitcoin was inefficient from 2011 to 2014, or Vidal-Tomás *et al.* (2019), who assume that Bitcoin becomes more inefficient over time.

The previous results show the existence of few statistically significant mean returns on different hours of each day of the week in the Bitcoin trading, but much more significant average cumulative returns in the following hours, especially on Mondays, Fridays and Sundays. In other words, we have found a kind of inefficiency in the cryptocurrency market linked to the different hours and days on which trades are materialised. However, there are still doubts surrounding this inefficiency, whether it is biased by the sample employed, and whether it could be used by investors to establish a profitable investment strategy.

Previous mean returns and average cumulative returns were estimated for the whole sample, but doubt remains whether the results would be different for alternative samples. For that reason, a robustness test is proposed, which consists of re-estimating the mean returns on each hour and day, those labelled in Table 10 as 0, but also the average cumulative returns 1, 2, 3, 4, 5, 6, 12, 18 and 24 hours following the hourly event of each day. We use three rolling windows of one, two and three years and test the null hypothesis that mean returns and average cumulative returns are zero for each sample. Obtaining a high number of significant tests would imply the existence of inefficiency over time. It would also provide us with information

about the time horizon, i.e. short, medium or long term over which an investment strategy could be planned.

Tables 10 to 12 show the percentages of statistically significant t-stats, at least at the 10% level, which are found in the whole sample after running 1-year, 2-year and 3-year rolling windows respectively. For the sake of brevity, we only report the results obtained for Mondays, Fridays and Sundays (the rest are available upon request) and only those time slots where we have previously found a greater number of statistically significant average cumulative returns. Therefore, the second column of each Table 10 to 12 reports the percentage of hourly mean returns which are significant for the event moment from 4 a.m. to 6 a.m. and from 12 p.m. to 3 p.m. on Mondays, from 12 a.m. to 2 a.m. and from 3 p.m. to 6 p.m. on Fridays, and finally from 9 a.m. to 3 p.m. on Sundays. The rest of the columns show the percentage of average cumulative returns relative to the post-event holding periods.

We find low percentages of statistically significant hourly mean returns, those defined as the event, for all the days, time slots or rolling windows considered. We even find some cases where there is no statistically significant mean return on Mondays or Sundays, but there is on Fridays. This is evidence of the robustness of the initial results where these mean returns appeared to be mostly insignificant.

The difference between Fridays and the other two days is greater on post-event average cumulative returns. The results of considering a 2-year rolling window on Fridays provide us with significance percentages higher than 90%. However, all of them are statistically significant on a time slot spanning from 4 hours to 24 hours following 3 p.m., as well as those 3 to 5 hours following 4 p.m. trades. On the other hand, percentages for Mondays and Sundays are not as high. We can find a few isolated cases of high percentages, but these are usually lower than Fridays or even zero. In other words, by considering these different rolling windows we add robustness to the results obtained mainly on Fridays, where there is a clear inefficiency, especially at 3 p.m. that can be exploited by investors.

Furthermore, these investors should also take into account the fact that higher percentages of statistically significant average returns are obtained when longer rolling windows are considered. From our point of view, this fact means that investments in Bitcoins should not be short term, despite their obvious volatility, but rather long term.

For this reason, we propose different investment strategies simply based on investing in Bitcoins on Fridays and holding that investment for a few hours. Considering the previous estimations where we find 100% of statistically significant mean returns, we focus on the results of investing exclu-

sively at 3 p.m. for 4, 5, 6, 12, 18 and 24 hours respectively for a 3-year rolling window period. We do not show the results for investing at 4 p.m. because they are almost identical to those obtained at 3 p.m. due to the overlapping periods.

We evaluate the performance of these investment strategies in terms of the Sharpe ratio, SR_t , which is defined by Sharpe (1966) as the average excess returns over the risk free rate (r_f) divided by their sample standard deviation:

$$SR_t = \frac{\hat{\mu}_t}{\sigma_t} = \frac{\mu_t - r_f}{\sigma_t} \quad (4)$$

We use this ratio because, as pointed out by García and Luger (2011), it is the most ubiquitous risk-adjusted measure used by financial market practitioners to rank investments and to evaluate the convenience of investment strategies in general. In order to evaluate the appropriateness of these investment strategies, we compare their results with those obtained by only investing from 3:00:00 p.m. to 3:59:59 p.m. on Fridays, which is the event time which is denoted as 0, but also a buy and hold strategy, denoted as BH, where only keeping the investment for three years is considered without restrictions on the day or the time when that investment is carried out.

The results for the Sharpe ratios of the proposed investment strategies are graphically shown in Figure 2. Values not annualized of the Sharpe ratios for investing 4, 5, 6, 12, 18 and 24 hours, respectively, denoted as Hold, for a 3-year rolling window period are reported on the Y-axis, but also those obtained by investing at the event time (Hold 0) and the buy and hold strategy (BH). The date where each ratio is obtained is reported on the X-axis. It should be mentioned that the first results appear to be from 2019, but are based on data from 2016 to 2018, inclusive, given the 3-year rolling window used. We find that the proposed strategies of investing on Fridays following the event –those that show 100% of statistically significant average returns– clearly outperform the performances of the other two investment options considered (buy and hold and only investing from 3:00:00 p.m. to 3:59:59 p.m. on Fridays). The buy and hold procedure without restrictions yields a positive performance that outperforms the bad one of investing on Fridays from 3:00:00 p.m. to 3:59:59 p.m., which is always negative. However, both are clearly outperformed by the options of holding the position in Bitcoins for 4 to 24 hours after the event using different time spans. Among them, holding the positions 4, 5, and 6 hours

after 3 p.m. appear to be the best performance options, especially the first one (4 hours), which is buy at 4 p.m. and sell at 7:59:59 p.m.

Additionally, we test for significant differences between the Sharpe ratios of the buy and hold procedure, which is commonly used as a benchmark, and each holding period for 4 to 24 hours due to their better performance results. We use the approach suggested by Jobson and Korkie (1981), corrected by Memmel (2003), which was also used by Gasbarro *et al.* (2007), DeMiguel *et al.* (2009), Daskalaki and Skiadopoulos (2011), Sun *et al.* (2016), and Cederburg *et al.* (2020), among others. Specifically, given two series *i* and *j*, and considering $\hat{\mu}_i$, $\hat{\mu}_j$, $\hat{\sigma}_i$, $\hat{\sigma}_j$, and $\hat{\sigma}_{ij}$ as the estimated means, standard deviations and covariance of excess returns over a period of length *T* respectively, the null hypothesis of equal Sharpe ratios

$H_0 : \frac{\hat{\mu}_i}{\hat{\sigma}_i} = \frac{\hat{\mu}_j}{\hat{\sigma}_j}$ is tested by using the following statistic:

$$\hat{z}_{ij} = \frac{\hat{\sigma}_j \hat{\mu}_i - \hat{\sigma}_i \hat{\mu}_j}{\sqrt{\hat{\theta}}} \tag{5}$$

where $\hat{\theta} = \frac{1}{T} \left(2\hat{\sigma}_i^2 \hat{\sigma}_j^2 - 2\hat{\sigma}_i \hat{\sigma}_j \hat{\sigma}_{ij} + \frac{1}{2} \hat{\mu}_i^2 \hat{\sigma}_j^2 + \frac{1}{2} \hat{\mu}_j^2 \hat{\sigma}_i^2 - \frac{\hat{\mu}_i \hat{\mu}_j}{\hat{\sigma}_i \hat{\sigma}_j} \hat{\sigma}_{ij}^2 \right)$.

The results for the z-values (Y-Axis), where Sharpe ratio of the buy and hold procedure are compared with each holding period for 4 to 24 hours, denoted as Z 4, Z 5, and so on, are reported in Figure 3. Once again, dates on the X-axis appear to be from 2019, but are based on data from 2016 to 2018, inclusive, given the 3-year rolling window employed. Based on the z-values, we state that the null of equal Sharpe ratios is clearly rejected in all cases and, therefore, holding the positions for 4 to 24 hours after 3 p.m. appears to be a good option for investors.

To sum up, we have revealed that there is a kind of day-of-the-week effect that is especially focused on Fridays and more precisely at 3 p.m. An investor who takes into account this circumstance would be able to obtain positive average cumulative returns during different holding times, but also would be able to outperform other investment strategies, such as the classical buy and hold, which does not take into account any special circumstances in the market. From our point of view, this seasonal behavior detected on Fridays is not surprising. It is similar to the documented evidence

about the day-of-the-week effect on traditional stock markets. Lakonishok and Levi (1982) argued that the explanation was related to the settlement procedure of the US stock market. However, the explanations provided by Lakonishok and Maberly (1990) in relation to certain behavioral patterns of individual investors make more sense and are applicable to other markets such as the cryptocurrencies one. According to these authors, individual investors need more time than specialists to make their investment decisions, especially sales decisions. Therefore, such decisions are usually made on weekends. On the other hand, buying decisions tend to be more concentrated before this period, mainly on Fridays.

Moreover, the significant seasonal behavior at 3 p.m. could be related to the late-informed investors hypothesis recently provided by Shen *et al.* (2022) to explain the existence of the momentum effect on bitcoin return time series. These authors argue that there are investors who get or process the information later or slowly. Thus, these late-informed investors usually trade during the last half hour before the close of the session in traditional markets. If these investors trade in the same direction, this will cause a price impact. Furthermore, if we join this argument to the one provided by Lakonishok and Marbely (1990) about individual investors, we could expect a positive price impact.

Conclusions

There is a big controversy surrounding the implications of the EMH and, therefore, there is vast empirical evidence questioning these implications. In that context, our paper provides a new point of view, where Bitcoin's hourly returns for each day of the week are analysed using a procedure based on the event study approach.

We analyse not only mean returns on Bitcoin for every hour of each day of the week looking for hourly patterns, but also their average cumulative returns up to some specific number of hours after each initial hour. Our first results show weak evidence of statistically significant mean returns for each hour on each day of the week. However, once the average cumulative returns after each hour are analysed, we find significant positive values, mostly on Fridays, which were corroborated through different robustness tests. Lastly, we have proved that holding investment positions from 4 to 24 hours in Bitcoin after 3 p.m. on Fridays yields better performances than other investment strategies, such as the traditional buy and hold position.

These findings shed some light on the empirical evidence by showing that complex methodologies are not necessary to know how an asset will

behave. However, investors and active professional managers can also use these techniques to add value to their investment strategies. Moreover, it may prove interesting in future research to investigate the robustness of our findings using alternative procedures and to look at their performance in investment strategies. In this sense, it would be interesting to analyse the reaction of Bitcoin to positive and negative returns or shocks and, therefore, to know whether there are overreaction or momentum effects. Moreover, this analysis could be applied to other crypto assets such as the Ethereum for the sake of finding a possible common behaviour, which could help investors to define their investment strategies.

References

- Aharon, D. Y., & Qadan, M. (2019). Bitcoin and the day-of-the-week effect. *Finance Research Letters*, *31*, 415–424. doi: 10.1016/j.frl.2018.12.004.
- Atkins, A. B., & Dyl, E. (1990). Price reversals, bid-ask spreads, and market efficiency. *Journal of Financial and Quantitative Analysis*, *25*, 535–547. doi: 10.2307/2331015.
- Ball, R., & Brown, P. (1968). An empirical evaluation of accounting numbers. *Journal of Accounting Research*, *6*(2), 159–178. doi: 10.2307/2490232.
- Bariviera, A. F. (2017). The inefficiency of Bitcoin revisited: a dynamic approach. *Economics Letters*, *161*, 1–4. doi: 10.1016/j.econlet.2017.09.013.
- Bariviera, A. F., & Merediz-Solà, I. (2021). Where do we stand in cryptocurrencies economic research? A survey based on hybrid analysis. *Journal of Economic Surveys*, *35*(2), 377–407. doi: 10.1111/joes.12412.
- Benou, G., & Richie, N. (2003). The reversal of large stock price declines: the case of large firms. *Journal of Economics and Finance*, *27*, 19–38. doi: 10.1007/BF02751588.
- Bogards, O., & Czudaj, R. (2020). The prevalence of price overreactions in the cryptocurrency market. *Journal of International Financial Markets, Institutions and Money*, *65*, 101194. doi: 10.1016/j.intfin.2020.101194.
- Bremer, M. A., & Sweeney, R. J. (1991). The reversal of large stock-price decreases. *Journal of Finance*, *46*, 747–754. doi: 10.1111/j.1540-6261.1991.tb02684.x.
- Brown, S. J., & Warner, J. B. (1985). Using daily stock returns: the case of event studies of event. *Journal of Financial Economics*, *14*(1), 3–31. doi: 10.1016/0304-405X(85)90042-X.
- Cai, J., Li, Y., & Qi, Y. (2006). The day-of-the-week effect: new evidence from the Chinese stock market. *Chinese Economy*, *39*(2), 71–88. doi: 10.2753/CES1097-1475390206.
- Caporale, G. M., Gilalana, L. A., Plastun, A. & Makarenko, I. (2016). Intraday anomalies and market efficiency: a trading robot analysis. *Computational Economics*, *47*(2), 275–295. doi: 10.1007/s10614-015-9484-9.

- Caporale, G. M., & Plastun, A. (2019). Price overreactions in the cryptocurrency market. *Journal of Economic Studies*, 46, 1137–1155. doi: 10.1108/JES-09-2018-0310.
- Caporale, G. M., & Plastun, A. (2020). Momentum effects in the cryptocurrency market after one-day abnormal returns. *Financial Markets and Portfolio Management*, 34, 251–266. doi: 10.1007/s11408-020-00357-1.
- Cederburg, S., O'Doherty, M. S., Wang, F., & Yan, Z. S. (2020). On the performance of volatility-managed portfolios. *Journal of financial Economics*, 138(1), 95–117. doi: 10.1016/j.jfineco.2020.04.015.
- Chiah, M., & Zhong, A. (2021). Tuesday blues and the day-of-the-week effect in stock returns. *Journal of Banking and Finance*, 133, 106243. doi: 10.1016/j.bankfin.2021.106243.
- Choi, D., & Hui, S. K. (2014). The role of surprise: understanding overreaction and underreaction to unanticipated events using in-play soccer betting market. *Journal of Economic Behavior and Organization*, 107(B), 614–629. doi: 10.1016/j.jebo.2014.02.009.
- Choudhry, T. (2001). Month of the year effect and January effect in pre-WWI stock returns: evidence from a non-linear GARCH model. *International Journal of Finance and Economics*, 6(1), 1–11. doi: 10.1002/ijfe.142.
- Corbet, S., Lucey, B., Urquhart, A., & Yarovaya, L. (2019). Cryptocurrencies as a financial asset: a systematic analysis. *International Review of Financial Analysis*, 62, 182–199. doi: 10.1016/j.irfa.2018.09.003.
- Cox, D. R., & Peterson, D. R. (1994). Stock returns following large one day declines. evidence on short-term reversals and longer term performance. *Journal of Finance*, 49, 255–267. doi: 10.1111/j.1540-6261.1994.tb04428.x.
- Cross, F. (1973). The behavior of stock prices on fridays and mondays. *Financial Analysts Journal*, 29(6), 67–69. doi: 10.2469/faj.v29.n6.67.
- Daskalaki, C., & Skiadopoulos, G. (2011). Should investors include commodities in their portfolios after all? New evidence. *Journal of Banking and Finance*, 35(10), 2606–2626. doi: 10.1016/j.jbankfin.2011.02.022.
- De Bondt, W. F. M., & Thaler, R. H. (1985). Does the stock market overreact? *Journal of Finance*, 40, 793–805. doi: 10.1111/j.1540-6261.1985.tb05004.x.
- De Bondt, W. F. M., & Thaler, R. H. (1987). Further evidence on investor overreaction and stock market seasonality. *Journal of Finance*, 42(3), 557–581. doi: 10.1111/j.1540-6261.1987.tb04569.x.
- DeMiguel, V., Garlappi, L., & Uppal, R. (2009). Optimal versus naive diversification: how inefficient is the 1/N portfolio strategy? *Review of Financial Studies*, 22(5), 1915–1953. doi: 10.1093/rfs/hhm075.
- Dissanaike, G. (1994). On the computation of returns in tests of the stock market overreaction hypothesis. *Journal of Banking and Finance*, 18(6), 1083–1094. doi: 10.1016/0378-4266(94)00061-1.
- Dodd, P., & Warner, J. (1983). On corporate governance: a study of proxy contests. *Journal of Financial Economics*, 11(1-4), 401–438. doi: 10.1016/0304-405X(83)90018-1.

- Dorflleitner, G., & Lung, C. (2018). Cryptocurrencies from the perspective of euro investors: a re-examination of diversification benefits and a new day-of-the-week effect. *Journal of Asset Management*, 19, 472–494. doi: 10.1057/s41260-018-0093-8.
- Doyle, J. R., & Chen, C. H. (2009). The wandering weekday effect in major stock major stock markets. *Journal of Banking and Finance*, 33(8), 1388–1399. doi: 10.1016/j.jbankfin.2009.02.002.
- Fama, E. (1965). The behavior of stock market prices. *Journal of Business*, 36(1), 34–105.
- Fama, E., Fisher, L., Jensen, M., & Roll, R. (1969). The adjustment of stock prices to new information. *International Economic Review*, 10(1), 1–21. doi: 10.2307/2525569.
- Fama, E. F. (1970). Efficient capital markets: a review of theory and empirical work. *Journal of Finance* 25(2), 383–417. doi: 2325486.
- Fung, A. K., Mok, D. M. Y., & Lam, K. (2000). Intraday price reversals for index futures in the US and Hong Kong. *Journal of Banking and Finance*, 24, 1179–1201. doi: 10.1016/S0378-4266(99)00072-2.
- García, L., & Luger, R. (2011). Dynamic correlations, estimation risk, and portfolio management during the financial crisis. *CEMFI Working Paper*, 1103. Retrieved from <https://www.cemfi.es/ftp/wp/1103.pdf>.
- Gasbarro, D., Wong, W., & Zumwalt, J. (2007). Stochastic dominance analysis of iShares. *European Journal of Finance*, 13(1), 89–101. doi: 10.1080/13518470601025243.
- Grant, J. L., Wolf, A., & Yu, S. (2005). Intraday price reversals in the U.S. stock index futures market: a 15-Year Study. *Journal of Banking and Finance*, 29, 1311–1327. doi: 10.1016/j.jbankfin.2004.04.006.
- Gultekin, M. N., & Gultekin, N. B. (1983). Stock market seasonality: international evidence. *Journal of Financial Economics*, 12(4), 469–481. doi: 10.1016/0304-405X(83)90044-2.
- Gunaratne, P. S. M., & Yonesawa, Y. (1997). Return reversals in the Tokyo Stock Exchange: a test of stock market overreaction. *Japan and the World Economy*, 9(3), 363–384. doi: 10.1016/S0922-1425(96)00256-3.
- Ising, J., Schiereck, D., Simpson, M., & Thomas, T. (2006). Stock returns following large 1-month declines and jumps: evidence of overoptimism in the German market. *Quarterly Review of Economics and Finance*, 46, 598–619. doi: 10.1016/j.qref.2006.02.005.
- Jalal, R. N., Alon, I., & Paltrinieri, A. (2022). A bibliometric review of cryptocurrencies as a financial asset. *Technology Analysis and Strategic Management*, Advance online publication. doi: 10.1080/09537325.2021.1939001.
- Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: implications for stock market efficiency. *Journal of Finance*, 48, 65–92. doi: 10.1111/j.1540-6261.1993.tb04702.x.
- Jobson, J., & Korkie, B.M. (1981). Performance hypothesis testing with the Sharpe and Treynor measures. *Journal of Finance*, 36(4), 889–908. doi: 10.2307/2327554.

- Kaiser, L. (2019). Seasonality in cryptocurrencies. *Finance Research Letters*, 31, 232–238. doi: 10.1016/j.frl.2018.11.007.
- Kosc, K., Sakowski, P., & Slepaczuk, R. (2019). Momentum and contrarian effects on the cryptocurrency market. *Physica A: Statistical Mechanics and its Applications*, 523(1), 691–701. doi: 10.1016/j.physa.2019.02.057.
- Kurihara, Y., & Fukushima, A. (2017). The market efficiency of Bitcoin: a weekly anomaly perspective. *Journal of Applied Finance and Banking*, 7(3), 57–64.
- Kyriazis, N. A. (2019). A survey on efficiency and profitable trading opportunities in cryptocurrency markets. *Journal of Risk and Financial Management*, 12(2), 67. doi: 10.3390/jrfm12020067.
- Lakonishok, J., & Levi, M. (1982). Weekend effects on stock returns: a note. *Journal of Finance*, 37, 883–889. doi: 10.2307/2327716.
- Lakonishok, J., & Maberly, E. (1990). The weekend effect: trading patterns of individual and institutional investors. *Journal of Finance*, 45, 231–243. doi: 10.2307/2328818.
- Lakonishok, J., & Smidt, S. (1988). Are seasonal anomalies real? A ninety-year perspective. *Review of Financial Studies*, 1(4), 403–425. doi: 10.1093/rfs/1.4.403.
- Lalwani, V., Sharma, U., & Chakraborty, M. (2019). Investor reaction to extreme price shocks in markets: a cross country examination. *IIMB Management Review*, 31(3), 258–267. doi: 10.1016/j.iimb.2019.03.004.
- Lasfer, M. A., Melnik, A., & Thomas, D. C. (2003). Short-term reaction of stock markets in stressful circumstances. *Journal of Banking and Finance* 27, 1959–1977. doi: 10.1016/S0378-4266(02)00313-8.
- López-Martín, C., Benito Muela, S., & Arguedas, R. (2021). Efficiency in cryptocurrency markets: new evidence. *Eurasian Economic Review*, 11, 403–431. doi: 10.1007/s40822-021-00182-5.
- Ma, D. L., & Tanizaki, H. (2019). The day-of-the-week effect on Bitcoin return and volatility. *Research in International Business and Finance*, 49, 127–136. doi: 10.1016/j.ribaf.2019.02.003.
- MacKinlay, G. (1997). Event studies in economics and finance. *Journal of Economic Literature*, 35(1), 13–39.
- Mommel, C. (2003). Performance hypothesis testing with the Sharpe ratio. *Finance Letters*, 1, 21–23.
- Merediz-Solà, I., & Bariviera, A.F. (2019). A bibliometric analysis of bitcoin scientific production. *Research in International Business and Finance*, 50, 294–305. doi: 10.1016/j.ribaf.2019.06.008.
- Miralles-Marcelo, J. L., Miralles-Quirós, J. L., & Miralles-Quirós, M. M. (2010). Intraday linkages between the Spanish and the US stock markets: evidence of an overreaction effect. *Applied Economics*, 42(2), 223–235. doi: 10.1080/00036840701579192.
- Miralles-Marcelo, J. L., Miralles-Quirós, J. L., & Miralles-Quirós, M. M. (2014). Intraday stock market behavior after shocks: the importance of bull and bear markets in Spain. *Journal of Behavioral Finance*, 15(2), 144–159. doi: 10.1080/15427560.2014.911743.

- Miwa, K. (2019). Trading hours extension and intraday price behavior. *International Review of Economics and Finance*, 64, 572–585. doi: 10.1016/j.irfe.2019.07.007.
- Nadarajah, S., & Chu, J. (2017). On the inefficiency of bitcoin. *Economic Letters*, 150, 6–9. doi: 10.1016/j.econlet.2016.10.033.
- Panagiotis, T., Renatas, K., & Bayasgalan, T. (2019). Momentum trading in cryptocurrencies: short-term returns and diversification benefits. *Economics Letters*, 191, 108728. doi: 10.1016/j.econlet.2019.108728.
- Phillip, A., Chan, J. S. K., & Peiris, S. (2018). A new look at cryptocurrencies. *Economics Letters*, 163, 6–9. doi: 10.1016/j.econlet.2017.11.020.
- Qadan, M., Aharon, D. Y., & Eichel, R. (2019). Seasonal patterns and calendar anomalies in the commodity market for natural resources. *Resources Policy*, 63, 101435. doi: 10.1016/j.resourpol.2019.101435.
- Qadan, M., & Idilbi-Bayaa, Y. (2021). The day-of-the-week effect on the volatility of commodities. *Resources Policy*, 71, 101980. doi: 10.1016/j.resourpol.2020.101980.
- Qadan, M., Aharon, D. Y., & Eichel, R. (2022). Seasonal and calendar effects and the price efficiency of cryptocurrencies. *Finance Research Letters*, 46(A), 102354. doi: 10.1016/j.frl.2021.102354.
- Qing, C., Xinyuan, L., & Xiaowu, Z. (2019). Cryptocurrency momentum effect: DFA and MF-DFA analysis. *Physica A: Statistical Mechanics and its Applications*, 526, 120847. doi: 10.1016/j.physa.2019.04.083.
- Roberts, H., (1967). *Statistical versus clinical prediction of the stock market*. Unpublished manuscript, CRSP, Chicago University of Chicago.
- Rozeff, M. S., & Kinney, W. R. (1976). Capital market seasonality: the case of stock returns. *Journal of Financial Economics*, 3(4), 379–402. doi: 10.1016/0304-405X(76)90028-3.
- Savor, P. G. (2012). Stocks returns after major price shocks: the impact of information. *Journal of Financial Economics*, 106(3), 645–659. doi: 10.1016/j.jfinec.2012.06.011.
- Samuelson, P. (1965). Proof that properly anticipated prices fluctuate randomly. *Industrial Management Review*, 6(2), 41–49.
- Sharpe, W. F. (1966). Mutual fund performance. *Journal of Business*, 39(1), 119–138. doi: 10.1086/294846.
- Shen, D., Urquhart, A., & Wang, P. (2022). Bitcoin intraday time series momentum. *Financial Review*, 57, 319–344. doi: 10.1111/fire.12290.
- Sias, R. W., & Starks, L. T. (1995). The day-of-the-week anomaly: the role of institutional investors. *Financial Analysts Journal*, 51(3), 58–67. doi: 10.2469/faj.v51.n3.1906.
- Sun, L., Najand, M., & Shen, J. (2016). Stock return predictability and investor sentiment: a high-frequency perspective. *Journal of Banking & Finance*, 73, 147–164. doi: 10.1016/j.jbankfin.2016.09.010.
- Tzouvanas, P., Kizys, R., & Tsend-Ayush, B. (2020). Momentum trading in cryptocurrencies: short-term returns and diversification benefits. *Economics Letters*, 191, 108728. doi: 10.1016/j.econlet.2019.108728.

- Urquhart, A. (2016). The inefficiency of Bitcoin. *Economics Letters*, 148, 80–82. doi: 10.1016/j.econlet.2016.09.019.
- Vidal-Tomás, D., & Ibáñez, A. (2018). Semi-strong efficiency of Bitcoin. *Finance Research Letters*, 27, 259–265. doi: 10.1016/j.frl.2018.03.013.
- Vidal-Tomás, D., Ibáñez, A. M., & Farinós, J. E. (2019). Weak efficiency of the cryptocurrency market: a market portfolio approach. *Applied Economics Letters*, 26(19), 1627–1633. doi: 10.1080/13504851.2019.1591583.
- Yukun, L., & Tsyvinski, A. (2021). Risks and returns of cryptocurrency. *Review of Financial Studies*, 34(6), 2689–2727. doi: 10.1093/rfs/hhaa113.
- Zaremba, A., Bilgin, M. H., Long, H., Mercik, A., & Szczygielski, J. J. (2021). Up or down? Short-term reversal, momentum, and liquidity effects in cryptocurrency markets. *International Review of Financial Analysis*, 78, 101908. doi: 10.1016/j.irfa.2021.101908.
- Zhang, J., Lai, Y., & Lin, J. (2017). The day-of-the-week effects of stock markets in different countries. *Finance Research Letters*, 20, 47–62. doi: 10.1016/j.frl.2016.09.006.

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Annex

Table 1. Descriptive Statistics

	MON	TUE	WED	THU	FRI	SAT	SUN	Equality test
Mean	0.000118	0.000062	0.000111	-0.000069	0.000271	-0.000022	0.000151	1.233781 (0.2852)
Median	0.000059	0.000089	0.000118	0.000037	0.000172	0.000000	0.000017	
Maximum	0.112861	0.090091	0.081589	0.174218	0.116951	0.082719	0.137429	
Minimum	-0.080323	-0.100692	-0.129037	-0.191412	-0.165158	-0.090405	-0.105168	
Std. Dev.	0.008586	0.008679	0.008912	0.009977	0.009377	0.007770	0.008235	
Skewness	0.046698	-0.243638	-0.866108	-1.668261	0.179037	-0.588944	0.531521	
Kurtosis	19.23252	18.51051	21.06381	62.52387	37.00046	19.00319	27.32623	
Jarque-Bera	82476.53	75374.58	103071.5	1112472.	363034.1	80594.20	185576.3	
P-value	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	

This table presents descriptive statistics for the hourly return series of the Bitcoin for the sample period from 1 January 2016 to 31 December 2021. The last column reports the mean and variance equality tests using the ANOVA and Levene statistics, respectively. Skewness and Kurtosis refer to the series skewness and kurtosis coefficients. The Jarque–Bera statistic tests the normality of the series.

Table 2. Mean returns for each hour and day

	MO	TU	WED	TH	FR	SAT	SUN
0	-0.0004 (-0.9574)	0.0005 (1.0977)	0.0002 (0.4854)	0.0001 (0.3465)	-0.0003 (-0.6370)	-0.0003 (-0.5812)	0.0002 (0.5396)
1	0.0004 (0.7897)	0.0002 (0.5640)	0.0010** (2.4868)	0.0001 (0.1336)	-0.0002 (-0.3519)	0.0004 (1.1148)	0.0003 (0.7594)
2	0.0004 (0.7583)	0.0007 (1.5932)	0.0001 (0.2569)	0.0002 (0.5313)	0.0007 (1.4322)	0.0002 (0.5681)	0.0000 (-0.0840)
3	-0.0002 (-0.4278)	-0.0004 (-0.7225)	-0.0001 (-0.2792)	0.0002 (0.4750)	0.0014** (2.1276)	-0.0001 (-0.3021)	0.0000 (0.0134)
4	-0.0004 (-0.9300)	0.0001 (0.2671)	-0.0001 (-0.3181)	-0.0001 (-0.2499)	0.0003 (0.6381)	0.0002 (0.3795)	-0.0001 (-0.1927)
5	0.0001 (0.1247)	-0.0004 (-0.8084)	0.0005 (1.0190)	-0.0006 (-0.7859)	0.0002 (0.3681)	0.0001 (0.1699)	0.0002 (0.4997)
6	0.0001 (0.2990)	0.0002 (0.3362)	0.0004 (0.9653)	0.0006 (1.1328)	-0.0003 (-0.7149)	0.0002 (0.3938)	-0.0001 (-0.2240)
7	0.0014** (2.3088)	0.0001 (0.1419)	0.0006 (0.9587)	0.0002 (0.3667)	0.0012** (2.0576)	-0.0002 (-0.5938)	-0.0013*** (-2.9290)
8	0.0007 (1.3168)	0.0001 (0.1858)	0.0005 (0.7945)	0.0002 (0.2633)	0.0000 (0.0300)	-0.0002 (-0.4680)	0.0005 (1.0329)

Table 2. Continued

	MO	TU	WED	TH	FR	SAT	SUN
9	-0.0006 (-1.1636)	-0.0007 (-1.1857)	-0.0006 (-1.1311)	0.0005 (0.7572)	0.0000 (0.0167)	0.0000 (0.0348)	-0.0005 (-1.0805)
10	0.0002 (0.4780)	0.0005 (1.1246)	0.0004 (0.6417)	-0.0003 (-0.5312)	0.0013** (2.0407)	0.0001 (0.2478)	0.0001 (0.1243)
11	-0.0002 (-0.5190)	0.0005 (1.0371)	0.0001 (0.1622)	-0.0008 (-1.1986)	-0.0001 (-0.1526)	0.0010** (2.2283)	0.0008 (1.4110)
12	-0.0007* (-1.6957)	0.0004 (0.6934)	0.0005 (1.0273)	-0.0004 (-0.8511)	-0.0011** (-2.4194)	0.0002 (0.4062)	0.0005 (1.0334)
13	0.0005 (1.0762)	-0.0002 (-0.4599)	-0.0005 (-0.9447)	0.0001 (0.1856)	-0.0003 (-0.7473)	0.0000 (0.1163)	0.0001 (0.3788)
14	0.0001 (0.2390)	-0.0001 (-0.2389)	0.0000 (0.0503)	0.0006 (1.3108)	0.0001 (0.2240)	0.0002 (0.6843)	0.0003 (0.5754)
15	0.0007 (1.3918)	-0.0003 (-0.5402)	-0.0003 (-0.5959)	-0.0004 (-0.7618)	-0.0007 (-1.2864)	-0.0004 (-0.7978)	0.0006 (1.1412)
16	0.0009** (2.2012)	0.0002 (0.3900)	0.0002 (0.4511)	0.0009* (1.9497)	0.0007 (1.0148)	0.0001 (0.1878)	0.0008 (1.1241)
17	-0.0005 (-0.9889)	-0.0001 (-0.1111)	0.0008 (1.4802)	0.0008* (1.6751)	0.0010** (2.0565)	0.0007* (1.6882)	0.0002 (0.3452)
18	0.0011** (2.0936)	0.0004 (0.8399)	0.0001 (0.1056)	-0.0015** (-2.0174)	0.0006 (1.2865)	-0.0005 (-1.1838)	0.0000 (-0.0065)
19	-0.0001 (-0.2240)	-0.0006 (-1.1254)	0.0001 (0.2021)	-0.0002 (-0.3862)	0.0015*** (3.1755)	-0.0007 (-1.3808)	0.0014** (2.5144)
20	-0.0004 (-0.9270)	0.0004 (0.7936)	0.0002 (0.3754)	-0.0007 (-1.2962)	0.0006 (1.1041)	0.0005 (1.3948)	0.0004 (0.8143)
21	-0.0004 (-1.0408)	-0.0004 (-0.8335)	-0.0002 (-0.3414)	0.0001 (0.1488)	-0.0004 (-0.9879)	-0.0007* (-1.8091)	-0.0001 (-0.3761)
22	-0.0002 (-0.6010)	-0.0001 (-0.2861)	-0.0008* (-1.8889)	0.0000 (-0.0680)	-0.0003 (-0.7290)	-0.0007 (-1.5716)	-0.0004 (-1.2355)
23	0.0004 (0.7518)	0.0005 (1.0198)	-0.0002 (-0.5356)	-0.0012** (-2.0650)	0.0004 (1.0705)	-0.0007 (-1.6388)	0.0000 (0.1091)

This table contains the mean returns and t-statistics in brackets from the 24 hours of each event day over the whole sample. Significant coefficients are denoted by ***, ** and * for 1%, 5% and 10% significance levels, respectively.

Table 3. Monday's post event holdings for each hour

	1	2	3	4	5	6	12	18	24
0	0.0004 (0.7897)	0.0007 (1.2126)	0.0005 (0.7906)	0.0001 (0.1831)	0.0002 (0.2070)	0.0004 (0.3268)	0.0011 (0.6465)	0.0040* (1.9585)	0.0037 (1.4571)
1	0.0004 (0.7583)	0.0002 (0.2858)	-0.0002 (-0.2792)	-0.0001 (-0.1467)	0.0000 (-0.0009)	0.0014 (1.2016)	0.0012 (0.7229)	0.0035* (1.7107)*	0.0036 (1.4078)
2	-0.0002 (-0.4278)	-0.0006 (-1.0212)	-0.0005 (-0.6383)	-0.0004 (-0.4123)	0.0010 (0.9945)	0.0018 (1.4898)	0.0010 (0.5624)	0.0027 (1.2966)	0.0039 (1.5375)
3	-0.0004 (-0.9300)	-0.0003 (-0.4574)	-0.0002 (-0.2278)	0.0012 (1.2447)	0.0019* (1.7070)*	0.0013 (1.0302)	0.0019 (1.1469)	0.0025 (1.1725)	0.0037 (1.5082)
4	0.0001 (0.1247)	0.0002 (0.3033)	0.0016* (1.7626)	0.0023** (2.1693)	0.0017 (1.3889)	0.0019 (1.3973)	0.0032* (1.9499)	0.0026 (1.2291)	0.0042* (1.7862)
5	0.0001 (0.2990)	0.0015** (2.0203)	0.0023** (2.3054)	0.0016 (1.4046)	0.0019 (1.4074)	0.0016 (1.2445)	0.0027* (1.6947)	0.0030 (1.3408)	0.0038 (1.5773)
6	0.0014** (2.3088)	0.0021*** (2.5960)	0.0015 (1.4418)	0.0017 (1.4645)	0.0015 (1.2637)	0.0008 (0.6104)	0.0036** (2.3051)	0.0033 (1.6002)	0.0038 (1.5973)
7	0.0007 (1.3168)	0.0001 (0.1020)	0.0003 (0.3444)	0.0001 (0.0988)	-0.0006 (-0.5646)	-0.0002 (-0.1432)	0.0021 (1.4190)	0.0022 (1.0909)	0.0025 (1.1093)
8	-0.0006 (-1.1636)	-0.0004 (-0.5678)	-0.0006 (-0.8016)	-0.0014 (-1.4390)	-0.0009 (-0.8806)	-0.0008 (-0.6843)	0.0009 (0.6157)	0.0021 (1.0652)	0.0018 (0.8316)
9	0.0002 (0.4780)	0.0000 (0.0248)	-0.0007 (-0.9011)	-0.0003 (-0.2885)	-0.0001 (-0.1431)	0.0006 (0.6191)	0.0012 (0.8080)	0.0024 (1.2499)	0.0018 (0.8425)
10	-0.0002 (-0.5190)	-0.0010 (-1.3992)	-0.0005 (-0.6650)	-0.0004 (-0.4435)	0.0004 (0.3963)	0.0013 (1.3842)	0.0007 (0.4567)	0.0023 (1.2380)	0.0020 (1.0264)
11	-0.0007* (-1.6957)	-0.0003 (-0.4918)	-0.0002 (-0.2209)	0.0006 (0.7618)	0.0015* (1.8682)	0.0011 (1.2167)	0.0013 (0.8562)	0.0021 (1.1937)	0.0028 (1.3963)
12	0.0005 (1.0762)	0.0006 (0.9055)	0.0013* (1.8201)	0.0022*** (2.7929)	0.0018** (2.1102)	0.0029*** (2.9822)	0.0025* (1.7010)	0.0030* (1.6706)	0.0039* (1.8053)
13	0.0001 (0.2390)	0.0009 (1.3487)	0.0018** (2.4111)	0.0013 (1.6328)	0.0024** (2.5666)	0.0023** (2.1820)	0.0023 (1.5275)	0.0026 (1.4929)	0.0032 (1.4419)
14	0.0007 (1.3918)	0.0017** (2.3971)	0.0012* (1.6466)	0.0023*** (2.5362)	0.0022** (2.1462)	0.0017* (1.6616)	0.0029* (1.8864)	0.0026 (1.3829)	0.0030 (1.2706)
15	0.0009** (2.2012)	0.0005 (0.7910)	0.0016** (2.0914)	0.0014* (1.6543)	0.0010 (1.0246)	0.0006 (0.5173)	0.0018 (1.1393)	0.0012 (0.6546)	0.0020 (0.8621)
16	-0.0005 (-0.9889)	0.0006 (0.9637)	0.0005 (0.5965)	0.0000 (0.0481)	-0.0004 (-0.3583)	-0.0006 (-0.5441)	0.0010 (0.6395)	0.0007 (0.4162)	0.0012 (0.5186)
17	0.0011** (2.0936)	0.0010 (1.2730)	0.0005 (0.5834)	0.0001 (0.0814)	-0.0002 (-0.1546)	0.0003 (0.2120)	0.0011 (0.7028)	0.0017 (0.9509)	0.0016 (0.6759)
18	-0.0001 (-0.2240)	-0.0006 (-0.8091)	-0.0010 (-1.2017)	-0.0012 (-1.3518)	-0.0008 (-0.6880)	-0.0003 (-0.2806)	0.0001 (0.0971)	0.0010 (0.5366)	0.0009 (0.4205)

Table 3. Continued

	1	2	3	4	5	6	12	18	24
19	-0.0004 (-0.9270)	-0.0009 (-1.3071)	-0.0011 (-1.4760)	-0.0007 (-0.6613)	-0.0002 (-0.1977)	0.0000 (0.0444)	0.0003 (0.2335)	0.0009 (0.4817)	0.0005 (0.2028)
20	-0.0004 (-1.0408)	-0.0007 (-1.1894)	-0.0002 (-0.2733)	0.0002 (0.2772)	0.0005 (0.5215)	0.0012 (1.1518)	0.0009 (0.5726)	0.0012 (0.6311)	0.0013 (0.5709)
21	-0.0002 (-0.6010)	0.0002 (0.2658)	0.0007 (0.8172)	0.0009 (1.0452)	0.0016* (1.6532)	0.0012 (1.1468)	0.0006 (0.3885)	0.0014 (0.7032)	0.0013 (0.5876)
22	0.0004 (0.7518)	0.0009 (1.3062)	0.0012 (1.4862)	0.0019** (2.1164)	0.0015 (1.4540)	0.0016 (1.4246)	0.0014 (0.9005)	0.0018 (0.8988)	0.0015 (0.6320)
23	0.0005 (1.0977)	0.0007 (1.3124)	0.0014** (2.2165)	0.0010 (1.2470)	0.0012 (1.1720)	0.0008 (0.7972)	0.0015 (0.9801)	0.0013 (0.6384)	0.0015 (0.6223)

This table contains the average cumulative returns and t-statistics in brackets from the 24 hours of the corresponding day up to different hourly holding times (1, 2, 3, 4, 5, 6, 12, 18 and 24) following the event over the whole sample. Significant coefficients are denoted by ***, ** and * for 1%, 5% and 10% significance levels, respectively.

Table 4. Tuesday's post event holdings for each hour

	1	2	3	4	5	6	12	18	24
0	0.0002 (0.5640)	0.0009 (1.5087)	0.0005 (0.6812)	0.0007 (0.7616)	0.0003 (0.3375)	0.0005 (0.4593)	0.0013 (0.8551)	0.0013 (0.6412)	0.0012 (0.5034)
1	0.0007 (1.5932)	0.0003 (0.4416)	0.0004 (0.5376)	0.0001 (0.0769)	0.0002 (0.2344)	0.0003 (0.2721)	0.0008 (0.5216)	0.0004 (0.2001)	0.0019 (0.8085)
2	-0.0004 (-0.7225)	-0.0003 (-0.3319)	-0.0006 (-0.8212)	-0.0005 (-0.5392)	-0.0004 (-0.4069)	-0.0003 (-0.2346)	0.0000 (0.0266)	0.0001 (0.0473)	0.0013 (0.5524)
3	0.0001 (0.2671)	-0.0002 (-0.3834)	-0.0001 (-0.1072)	0.0000 (-0.0131)	0.0001 (0.0826)	-0.0006 (-0.5299)	0.0002 (0.1114)	0.0001 (0.0633)	0.0016 (0.7031)
4	-0.0004 (-0.8084)	-0.0002 (-0.3321)	-0.0002 (-0.2141)	0.0000 (-0.0513)	-0.0008 (-0.7763)	-0.0002 (-0.2275)	0.0002 (0.1367)	-0.0001 (-0.0677)	0.0013 (0.6033)
5	0.0002 (0.3362)	0.0002 (0.3694)	0.0003 (0.3742)	-0.0004 (-0.4111)	0.0001 (0.1172)	0.0007 (0.6135)	0.0005 (0.3148)	0.0007 (0.3415)	0.0022 (0.9206)
6	0.0001 (0.1419)	0.0002 (0.2196)	-0.0005 (-0.6184)	0.0000 (-0.0272)	0.0005 (0.4808)	0.0009 (0.7458)	0.0008 (0.4844)	0.0007 (0.3563)	0.0024 (0.9821)
7	0.0001 (0.1858)	-0.0006 (-0.8038)	-0.0001 (-0.1010)	0.0005 (0.4471)	0.0008 (0.7404)	0.0006 (0.4504)	0.0001 (0.0734)	0.0016 (0.8165)	0.0029 (1.1867)
8	-0.0007 (-1.1857)	-0.0002 (-0.2393)	0.0003 (0.3533)	0.0007 (0.6653)	0.0005 (0.3843)	0.0004 (0.2784)	0.0004 (0.2503)	0.0016 (0.8518)	0.0033 (1.3858)
9	0.0005 (1.1246)	0.0011 (1.5626)	0.0014* (1.7318)	0.0012 (1.2031)	0.0011 (1.0047)	0.0008 (0.7019)	0.0008 (0.5005)	0.0022 (1.2857)	0.0034 (1.4646)

Table 4. Continued

	1	2	3	4	5	6	12	18	24
10	0.0005 (1.0371)	0.0009 (1.2232)	0.0007 (0.7347)	0.0006 (0.5432)	0.0003 (0.2637)	0.0005 (0.3963)	0.0001 (0.0748)	0.0016 (0.8755)	0.0033 (1.3471)
11	0.0004 (0.6934)	0.0001 (0.1484)	0.0000 (0.0072)	-0.0003 (-0.2450)	-0.0001 (-0.0781)	-0.0001 (-0.1185)	0.0000 (0.0174)	0.0015 (0.7698)	0.0028 (1.1605)
12	-0.0002 (-0.4599)	-0.0003 (-0.4634)	-0.0006 (-0.7276)	-0.0004 (-0.4812)	-0.0005 (-0.4576)	-0.0001 (-0.0790)	-0.0001 (-0.0925)	0.0015 (0.7938)	0.0029 (1.2136)
13	-0.0001 (-0.2389)	-0.0004 (-0.6093)	-0.0002 (-0.2654)	-0.0003 (-0.2785)	0.0002 (0.1817)	-0.0004 (-0.4145)	0.0011 (0.7658)	0.0024 (1.2019)	0.0027 (1.1475)
14	-0.0003 (-0.5402)	-0.0001 (-0.1521)	-0.0002 (-0.1881)	0.0003 (0.3350)	-0.0003 (-0.3408)	0.0001 (0.0492)	0.0013 (0.9496)	0.0029 (1.5019)	0.0029 (1.2525)
15	0.0002 (0.3900)	0.0001 (0.1573)	0.0005 (0.7558)	-0.0001 (-0.0915)	0.0003 (0.3199)	-0.0001 (-0.0628)	0.0014 (1.0875)	0.0026 (1.3329)	0.0028 (1.2550)
16	-0.0001 (-0.1111)	0.0004 (0.5598)	-0.0002 (-0.3001)	0.0001 (0.1637)	-0.0002 (-0.2388)	-0.0003 (-0.3281)	0.0011 (0.8411)	0.0028 (1.4342)	0.0029 (1.2807)
17	0.0004 (0.8399)	-0.0002 (-0.2826)	0.0002 (0.2672)	-0.0002 (-0.1921)	-0.0003 (-0.2905)	0.0002 (0.1617)	0.0016 (1.1206)	0.0030 (1.4554)	0.0037 (1.6134)
18	-0.0006 (-1.1254)	-0.0002 (-0.3065)	-0.0006 (-0.7695)	-0.0007 (-0.8036)	-0.0002 (-0.2479)	-0.0001 (-0.0586)	0.0016 (1.1146)	0.0030 (1.4797)	0.0034 (1.4349)
19	0.0004 (0.7936)	0.0000 (0.0296)	-0.0001 (-0.1345)	0.0004 (0.4234)	0.0005 (0.6272)	0.0015 (1.5511)	0.0028* (1.6936)	0.0032 (1.5147)	0.0041* (1.6491)
20	-0.0004 (-0.8335)	-0.0005 (-0.8278)	0.0000 (-0.0447)	0.0001 (0.2118)	0.0011 (1.3413)	0.0012 (1.3558)	0.0029* (1.8004)	0.0028 (1.3984)	0.0039 (1.5808)
21	-0.0001 (-0.2861)	0.0003 (0.5622)	0.0005 (0.8457)	0.0015** (2.0427)	0.0016** (1.9728)	0.0015* (1.7227)	0.0027 (1.6365)	0.0029 (1.4359)	0.0041* (1.6546)
22	0.0005 (1.0198)	0.0006 (1.3137)	0.0016*** (2.6693)	0.0017** (2.4709)	0.0016** (2.0826)	0.0014* (1.6556)	0.0032* (1.9053)	0.0032 (1.6388)	0.0033 (1.4065)
23	0.0002 (0.4854)	0.0011** (2.2602)	0.0013** (2.0174)	0.0011 (1.5994)	0.0010 (1.1667)	0.0014 (1.4443)	0.0028* (1.6782)	0.0035* (1.7881)	0.0027 (1.1174)

This table contains the average cumulative returns and t-statistics in brackets from the 24 hours of the corresponding day up to different hourly holding times (1, 2, 3, 4, 5, 6, 12, 18 and 24) following the event over the whole sample. Significant coefficients are denoted by ***, ** and * for 1%, 5% and 10% significance levels, respectively.

Table 5. Wednesday's post event holdings for each hour

	1	2	3	4	5	6	12	18	24
0	0.0010** (2.4868)	0.0011* (1.8898)	0.0010 (1.3424)	0.0008 (0.9465)	0.0013 (1.2469)	0.0016 (1.5133)	0.0031* (1.7312)	0.0034 (1.6347)	0.0026 (1.0485)
1	0.0001 (0.2569)	0.0000 (-0.0117)	-0.0002 (-0.2016)	0.0003 (0.3165)	0.0007 (0.6542)	0.0013 (1.0292)	0.0017 (0.9300)	0.0026 (1.1981)	0.0017 (0.7058)
2	-0.0001 (-0.2792)	-0.0003 (-0.4349)	0.0002 (0.2407)	0.0006 (0.6285)	0.0012 (1.0125)	0.0017 (1.3446)	0.0016 (0.9269)	0.0026 (1.2393)	0.0018 (0.7665)
3	-0.0001 (-0.3181)	0.0003 (0.4443)	0.0007 (0.8492)	0.0013 (1.1865)	0.0018 (1.5238)	0.0012 (0.9150)	0.0014 (0.7695)	0.0026 (1.1709)	0.0022 (0.8866)
4	0.0005 (1.0190)	0.0008 (1.3839)	0.0015 (1.5386)	0.0019* (1.8863)	0.0013 (1.1911)	0.0017 (1.3484)	0.0018 (1.0273)	0.0019 (0.8933)	0.0022 (0.9098)
5	0.0004 (0.9653)	0.0010 (1.2487)	0.0015* (1.6537)	0.0009 (0.8843)	0.0013 (1.0786)	0.0014 (1.0626)	0.0021 (1.2039)	0.0012 (0.5794)	0.0011 (0.4441)
6	0.0006 (0.9587)	0.0011 (1.4031)	0.0005 (0.5461)	0.0009 (0.8123)	0.0010 (0.8142)	0.0015 (1.1478)	0.0018 (1.0071)	0.0010 (0.4645)	0.0014 (0.5544)
7	0.0005 (0.7945)	-0.0001 (-0.1380)	0.0003 (0.2493)	0.0004 (0.2954)	0.0008 (0.6590)	0.0004 (0.2792)	0.0012 (0.7014)	0.0004 (0.1915)	0.0010 (0.3725)
8	-0.0006 (-1.1311)	-0.0002 (-0.2840)	-0.0001 (-0.1022)	0.0004 (0.3384)	-0.0001 (-0.0910)	-0.0001 (-0.0597)	0.0010 (0.5525)	0.0001 (0.0706)	0.0007 (0.2487)
9	0.0004 (0.6417)	0.0005 (0.5227)	0.0009 (0.9705)	0.0005 (0.4552)	0.0005 (0.4119)	0.0002 (0.1328)	0.0014 (0.7617)	0.0010 (0.4818)	0.0017 (0.6347)
10	0.0001 (0.1622)	0.0006 (0.7663)	0.0001 (0.1325)	0.0001 (0.1349)	-0.0002 (-0.1566)	0.0001 (0.0488)	0.0002 (0.1030)	0.0005 (0.2422)	0.0011 (0.4052)
11	0.0005 (1.0273)	0.0000 (-0.0001)	0.0000 (0.0355)	-0.0003 (-0.3083)	-0.0001 (-0.0511)	0.0007 (0.6746)	-0.0002 (-0.1102)	-0.0002 (-0.1141)	0.0001 (0.0507)
12	-0.0005 (-0.9447)	-0.0004 (-0.6340)	-0.0008 (-0.8392)	-0.0005 (-0.5107)	0.0003 (0.2660)	0.0003 (0.2781)	-0.0005 (-0.3188)	0.0000 (-0.0204)	-0.0008 (-0.2776)
13	0.0000 (0.0503)	-0.0003 (-0.3629)	-0.0001 (-0.0542)	0.0007 (0.7250)	0.0008 (0.7018)	0.0009 (0.7171)	0.0000 (0.0161)	0.0006 (0.2814)	-0.0002 (-0.0733)
14	-0.0003 (-0.5959)	-0.0001 (-0.1058)	0.0007 (0.8425)	0.0008 (0.7848)	0.0008 (0.7895)	0.0010 (0.8676)	0.0002 (0.1528)	0.0008 (0.3316)	0.0004 (0.1532)
15	0.0002 (0.4511)	0.0010 (1.4739)	0.0011 (1.2589)	0.0012 (1.2564)	0.0014 (1.2716)	0.0012 (1.0981)	0.0008 (0.5393)	0.0016 (0.7206)	0.0003 (0.1261)
16	0.0008 (1.4802)	0.0008 (1.0918)	0.0009 (1.0781)	0.0011 (1.1755)	0.0010 (1.0036)	0.0001 (0.1046)	0.0004 (0.2783)	0.0010 (0.4658)	0.0010 (0.3751)
17	0.0001 (0.1056)	0.0001 (0.2060)	0.0003 (0.4133)	0.0002 (0.2012)	-0.0007 (-0.6823)	-0.0009 (-0.8635)	-0.0010 (-0.5656)	-0.0006 (-0.2539)	0.0010 (0.3690)
18	0.0001 (0.2021)	0.0003 (0.4068)	0.0001 (0.1504)	-0.0007 (-0.7917)	-0.0010 (-0.9208)	-0.0008 (-0.7324)	-0.0004 (-0.2078)	-0.0011 (-0.4515)	-0.0006 (-0.1886)

Table 5. Continued

	1	2	3	4	5	6	12	18	24
19	0.0002 (0.3754)	0.0000 (0.0484)	-0.0008 (-1.0189)	-0.0010 (-1.1215)	-0.0009 (-0.8966)	-0.0009 (-0.8302)	-0.0002 (-0.1213)	-0.0011 (-0.4479)	-0.0009 (-0.2866)
20	-0.0002 (-0.3414)	-0.0010 (-1.5677)	-0.0012 (-1.5985)	-0.0011 (-1.2291)	-0.0010 (-1.1412)	-0.0008 (-0.8434)	-0.0003 (-0.1383)	-0.0006 (-0.2697)	-0.0018 (-0.5472)
21	-0.0008* (-1.8889)	-0.0011* (-1.7152)	-0.0009 (-1.2516)	-0.0009 (-1.1763)	-0.0007 (-0.7733)	-0.0004 (-0.3966)	0.0003 (0.1843)	-0.0009 (-0.3736)	-0.0015 (-0.5133)
22	-0.0002 (-0.5356)	-0.0001 (-0.1649)	0.0000 (-0.0572)	0.0002 (0.2459)	0.0004 (0.4500)	0.0003 (0.2655)	0.0009 (0.4681)	0.0009 (0.3633)	-0.0007 (-0.2520)
23	0.0001 (0.3465)	0.0002 (0.3725)	0.0004 (0.6665)	0.0006 (0.7779)	0.0005 (0.5142)	-0.0001 (-0.0543)	0.0003 (0.1453)	0.0019 (0.7975)	-0.0017 (-0.5810)

This table contains the average cumulative returns and t-statistics in brackets from the 24 hours of the corresponding day up to different hourly holding times (1, 2, 3, 4, 5, 6, 12, 18 and 24) following the event over the whole sample. Significant coefficients are denoted by ***, ** and * for 1%, 5% and 10% significance levels, respectively.

Table 6. Thursday's post event holdings for each hour

	1	2	3	4	5	6	12	18	24
0	0.0001 (0.1336)	0.0003 (0.4873)	0.0005 (0.6274)	0.0004 (0.3845)	-0.0002 (-0.1577)	0.0004 (0.3200)	-0.0003 (-0.1254)	0.0003 (0.0949)	-0.0021 (-0.7398)
1	0.0002 (0.5313)	0.0005 (0.6580)	0.0003 (0.3718)	-0.0003 (-0.2218)	0.0004 (0.2966)	0.0006 (0.4020)	-0.0002 (-0.1098)	0.0000 (-0.0112)	-0.0024 (-0.8458)
2	0.0002 (0.4750)	0.0001 (0.1556)	-0.0005 (-0.4494)	0.0002 (0.1410)	0.0004 (0.2776)	0.0006 (0.3313)	0.0002 (0.0948)	-0.0010 (-0.3231)	-0.0018 (-0.6507)
3	-0.0001 (-0.2499)	-0.0007 (-0.8047)	-0.0001 (-0.0682)	0.0002 (0.1195)	0.0003 (0.2007)	0.0008 (0.5161)	-0.0005 (-0.2285)	-0.0011 (-0.4210)	-0.0007 (-0.2577)
4	-0.0006 (-0.7859)	0.0001 (0.0568)	0.0003 (0.2500)	0.0004 (0.3222)	0.0009 (0.6722)	0.0006 (0.4314)	0.0006 (0.2928)	-0.0010 (-0.4293)	-0.0002 (-0.0883)
5	0.0006 (1.1328)	0.0009 (1.0561)	0.0010 (0.9833)	0.0015 (1.3746)	0.0012 (1.0141)	0.0004 (0.2717)	0.0019 (1.1070)	-0.0016 (-0.7240)	0.0005 (0.2171)
6	0.0002 (0.3667)	0.0004 (0.4438)	0.0008 (0.9228)	0.0006 (0.5437)	-0.0003 (-0.2201)	-0.0007 (-0.5069)	-0.0002 (-0.0997)	-0.0026 (-1.2106)	-0.0004 (-0.1767)
7	0.0002 (0.2633)	0.0006 (0.8021)	0.0003 (0.3580)	-0.0005 (-0.4625)	-0.0009 (-0.7520)	-0.0008 (-0.6667)	-0.0006 (-0.3426)	-0.0030 (-1.4744)	0.0005 (0.2235)
8	0.0005 (0.7572)	0.0002 (0.2393)	-0.0007 (-0.6287)	-0.0011 (-0.9180)	-0.0010 (-0.8358)	-0.0004 (-0.2863)	-0.0015 (-0.7242)	-0.0024 (-1.1507)	0.0004 (0.1672)
9	-0.0003 (-0.5312)	-0.0011 (-1.3520)	-0.0016 (-1.5206)	-0.0015 (-1.4507)	-0.0008 (-0.7609)	-0.0012 (-1.0327)	-0.0019 (-1.0425)	-0.0015 (-0.7353)	-0.0001 (-0.0238)

Table 6. Continued

	1	2	3	4	5	6	12	18	24
10	-0.0008 (-1.1986)	-0.0013 (-1.4229)	-0.0012 (-1.3204)	-0.0005 (-0.5451)	-0.0010 (-0.8568)	-0.0001 (-0.0575)	-0.0016 (-0.9966)	-0.0009 (-0.4288)	0.0016 (0.6836)
11	-0.0004 (-0.8511)	-0.0003 (-0.5395)	0.0003 (0.4226)	-0.0001 (-0.1251)	0.0008 (0.8563)	0.0016 (1.5249)	-0.0020 (-1.2060)	0.0002 (0.0888)	0.0023 (1.0143)
12	0.0001 (0.1856)	0.0007 (1.3012)	0.0003 (0.4090)	0.0012 (1.4871)	0.0020** (2.1339)	0.0005 (0.4121)	-0.0019 (-1.1777)	0.0003 (0.1468)	0.0017 (0.7608)
13	0.0006 (1.3108)	0.0002 (0.3229)	0.0011 (1.4594)	0.0019** (2.1378)	0.0004 (0.3488)	0.0002 (0.1463)	-0.0021 (-1.4705)	0.0013 (0.7507)	0.0012 (0.5613)
14	-0.0004 (-0.7618)	0.0005 (0.7536)	0.0013* (1.6557)	-0.0002 (-0.1841)	-0.0004 (-0.3368)	-0.0012 (-0.7352)	-0.0020 (-1.3531)	0.0008 (0.4017)	0.0007 (0.3423)
15	0.0009* (1.9497)	0.0017*** (2.5849)	0.0002 (0.2033)	0.0000 (-0.0270)	-0.0007 (-0.5269)	-0.0006 (-0.5427)	-0.0002 (-0.1659)	0.0012 (0.6366)	0.0005 (0.2293)
16	0.0008* (1.6751)	-0.0007 (-0.7859)	-0.0009 (-0.8730)	-0.0016 (-1.1966)	-0.0015 (-1.3750)	-0.0015 (-1.5236)	-0.0008 (-0.5387)	0.0016 (0.8837)	0.0003 (0.1428)
17	-0.0015 (-2.0174)	-0.0017* (-1.7886)	-0.0024** (-1.8993)	-0.0023** (-2.2005)	-0.0023** (-2.4683)	-0.0035*** (-2.9763)	-0.0014 (-0.9202)	0.0007 (0.3755)	0.0005 (0.2400)
18	-0.0002 (-0.3862)	-0.0009 (-1.1812)	-0.0008 (-0.9654)	-0.0009 (-0.9585)	-0.0021** (-2.1098)	-0.0024** (-2.1442)	-0.0002 (-0.1469)	0.0012 (0.6066)	0.0026 (1.1674)
19	-0.0007 (-1.2962)	-0.0006 (-0.7938)	-0.0006 (-0.7332)	-0.0018 (-1.9194)	-0.0021 (-1.9089)	-0.0023** (-2.0090)	0.0011 (0.6931)	0.0010 (0.5273)	0.0044* (1.9146)
20	0.0001 (0.1488)	0.0001 (0.0887)	-0.0011 (-1.1795)	-0.0014 (-1.2986)	-0.0016 (-1.3436)	-0.0009 (-0.6503)	0.0019 (1.0150)	0.0019 (0.8791)	0.0057** (2.2710)
21	0.0000 (-0.0680)	-0.0012* (-1.8255)	-0.0015* (-1.8656)	-0.0017** (-2.0215)	-0.0010 (-0.9871)	0.0004 (0.3405)	0.0018 (1.1244)	0.0011 (0.5588)	0.0052** (2.2149)
22	-0.0012** (-2.0650)	-0.0015** (-2.0957)	-0.0017** (-2.3083)	-0.0010 (-1.0787)	0.0004 (0.3994)	0.0008 (0.6235)	0.0032** (1.9853)	0.0019 (0.9497)	0.0049** (2.1358)
23	-0.0003 (-0.6370)	-0.0005 (-0.7124)	0.0002 (0.2627)	0.0016 (1.5989)	0.0020 (1.6039)	0.0021 (1.6322)	0.0043*** (2.6324)	0.0041** (2.0205)	0.0066*** (2.7823)

This table contains the average cumulative returns and t-statistics in brackets from the 24 hours of the corresponding day up to different hourly holding times (1, 2, 3, 4, 5, 6, 12, 18 and 24) following the event over the whole sample. Significant coefficients are denoted by ***, ** and * for 1%, 5% and 10% significance levels, respectively.

Table 7. Friday's post event holdings for each hour

	1	2	3	4	5	6	12	18	24
0	-0.0002 (-0.3519)	0.0005 (0.7633)	0.0019** (2.2033)	0.0023** (2.0239)	0.0024** (1.9897)	0.0021 (1.6055)	0.0035** (2.2153)	0.0050** (2.4638)	0.0066*** (2.7452)
1	0.0007 (1.4322)	0.0021*** (2.8309)	0.0025** (2.4460)	0.0026** (2.3537)	0.0023* (1.8796)	0.0035*** (2.8245)	0.0034** (1.9840)	0.0067*** (3.3644)	0.0072*** (2.9482)
2	0.0014** (2.1276)	0.0017* (1.9062)	0.0019* (1.8173)	0.0016 (1.3658)	0.0027** (2.3401)	0.0028** (2.0961)	0.0028 (1.5659)	0.0065*** (2.9973)	0.0066*** (2.7298)
3	0.0003 (0.6381)	0.0005 (0.7221)	0.0002 (0.2363)	0.0014 (1.5147)	0.0014 (1.2586)	0.0014 (1.1477)	0.0007 (0.3915)	0.0048** (2.2134)	0.0051** (2.1058)
4	0.0002 (0.3681)	-0.0001 (-0.2249)	0.0010 (1.3327)	0.0010 (1.0110)	0.0010 (0.8496)	0.0024* (1.7491)	0.0011 (0.6061)	0.0041* (1.9450)	0.0050** (2.1108)
5	-0.0003 (-0.7149)	0.0008 (1.2419)	0.0009 (0.8244)	0.0009 (0.7027)	0.0022 (1.6375)	0.0021 (1.5427)	0.0019 (1.0600)	0.0044** (2.0135)	0.0049** (2.1149)
6	0.0012** (2.0576)	0.0012 (1.2438)	0.0012 (1.0161)	0.0025* (1.9311)	0.0025* (1.8553)	0.0014 (1.0195)	0.0028 (1.5807)	0.0044** (1.9650)	0.0054** (2.3766)
7	0.0000 (0.0300)	0.0000 (0.0347)	0.0014 (1.3043)	0.0013 (1.1419)	0.0002 (0.2018)	-0.0001 (-0.0755)	0.0032** (1.9615)	0.0037* (1.7764)	0.0040* (1.8813)
8	0.0000 (0.0167)	0.0013 (1.4574)	0.0013 (1.3115)	0.0002 (0.2086)	-0.0001 (-0.0961)	0.0000 (0.0007)	0.0038** (2.1168)	0.0039* (1.9055)	0.0038* (1.7412)
9	0.0013** (2.0407)	0.0013 (1.5664)	0.0002 (0.2414)	-0.0001 (-0.1226)	0.0000 (-0.0087)	-0.0007 (-0.5122)	0.0034** (1.9847)	0.0037* (1.9308)	0.0038* (1.7252)
10	-0.0001 (-0.1526)	-0.0011* (-1.8525)	-0.0015* (-1.8618)	-0.0013 (-1.5212)	-0.0020* (-1.8648)	-0.0013 (-1.1457)	0.0018 (1.0898)	0.0026 (1.4501)	0.0026 (1.2563)
11	-0.0011** (-2.4194)	-0.0014** (-1.9844)	-0.0013 (-1.5525)	-0.0019* (-1.9007)	-0.0012 (-1.0961)	-0.0002 (-0.1915)	0.0023 (1.3569)	0.0028 (1.5396)	0.0037* (1.7375)
12	-0.0003 (-0.7473)	-0.0002 (-0.3357)	-0.0009 (-1.0169)	-0.0002 (-0.1826)	0.0008 (0.7284)	0.0014 (1.2923)	0.0030* (1.9437)	0.0040** (2.4019)	0.0049** (2.5094)
13	0.0001 (0.2240)	-0.0005 (-0.7870)	0.0002 (0.1706)	0.0012 (1.1043)	0.0018* (1.6754)	0.0033*** (3.1169)	0.0038** (2.5233)	0.0041** (2.4555)	0.0053*** (2.7393)
14	-0.0007 (-1.2864)	0.0000 (0.0444)	0.0010 (1.0896)	0.0017* (1.7403)	0.0032*** (3.2648)	0.0038*** (3.2192)	0.0039*** (2.7176)	0.0038** (2.2123)	0.0054*** (2.8702)
15	0.0007 (1.0148)	0.0017** (1.9691)	0.0023** (2.5285)	0.0038*** (3.9817)	0.0044*** (3.8309)	0.0040*** (3.4648)	0.0044*** (3.0944)	0.0045*** (2.6790)	0.0057*** (3.0391)
16	0.0010** (2.0565)	0.0016** (2.5478)	0.0031*** (4.3892)	0.0037*** (3.8348)	0.0033*** (3.3588)	0.0031*** (2.7552)	0.0039*** (2.8188)	0.0039** (2.3252)	0.0050*** (2.7190)
17	0.0006 (1.2865)	0.0021*** (3.2781)	0.0027*** (2.9625)	0.0023** (2.5383)	0.0021** (2.0031)	0.0025** (2.2329)	0.0030** (2.1486)	0.0039** (2.2079)	0.0048** (2.5513)
18	0.0015*** (3.1755)	0.0021*** (2.6336)	0.0017** (2.1321)	0.0014 (1.5220)	0.0019* (1.7873)	0.0016 (1.4078)	0.0026* (1.9389)	0.0035** (2.0424)	0.0036** (1.9620)

Table 7. Continued

	1	2	3	4	5	6	12	18	24
19	0.0006 (1.1041)	0.0002 (0.3187)	-0.0001 (-0.0963)	0.0003 (0.3841)	0.0001 (0.0834)	0.0005 (0.4847)	0.0008 (0.5773)	0.0020 (1.1835)	0.0014 (0.7112)
20	-0.0004 (-0.9879)	-0.0007 (-1.0846)	-0.0002 (-0.3239)	-0.0005 (-0.5578)	-0.0001 (-0.1043)	0.0001 (0.1199)	0.0000 (0.0097)	0.0017 (0.9869)	0.0013 (0.6791)
21	-0.0003 (-0.7290)	0.0001 (0.2712)	-0.0001 (-0.1509)	0.0003 (0.3848)	0.0005 (0.6254)	0.0004 (0.4063)	0.0004 (0.3124)	0.0016 (1.0056)	0.0010 (0.5325)
22	0.0004 (1.0705)	0.0002 (0.2422)	0.0006 (0.8081)	0.0008 (1.0652)	0.0007 (0.7538)	0.0009 (0.8435)	0.0008 (0.6049)	0.0020 (1.2394)	0.0006 (0.2992)
23	-0.0003 (-0.5812)	0.0001 (0.2936)	0.0004 (0.6103)	0.0002 (0.3425)	0.0004 (0.5092)	0.0005 (0.5381)	0.0014 (1.0476)	0.0023 (1.4670)	-0.0005 (-0.2742)

This table contains the average cumulative returns and t-statistics in brackets from the 24 hours of the corresponding day up to different hourly holding times (1, 2, 3, 4, 5, 6, 12, 18 and 24) following the event over the whole sample. Significant coefficients are denoted by ***, ** and * for 1%, 5% and 10% significance levels, respectively.

Table 8. Saturday's post event holdings for each hour

	1	2	3	4	5	6	12	18	24
0	0.0004 (1.1148)	0.0006 (1.2429)	0.0005 (0.8229)	0.0007 (0.9110)	0.0008 (0.8560)	0.0010 (1.0211)	0.0019 (1.3249)	0.0020 (1.3176)	-0.0001 (-0.0340)
1	0.0002 (0.5681)	0.0001 (0.1645)	0.0003 (0.3889)	0.0004 (0.4191)	0.0005 (0.6283)	0.0003 (0.3037)	0.0015 (1.1156)	0.0009 (0.5503)	-0.0002 (-0.1116)
2	-0.0001 (-0.3021)	0.0001 (0.1115)	0.0002 (0.1868)	0.0003 (0.4114)	0.0001 (0.0949)	-0.0001 (-0.1027)	0.0015 (1.1450)	0.0012 (0.7441)	-0.0005 (-0.2413)
3	0.0002 (0.3795)	0.0003 (0.3912)	0.0005 (0.6155)	0.0002 (0.2489)	0.0000 (0.0262)	0.0000 (0.0368)	0.0012 (0.9276)	0.0006 (0.3810)	-0.0003 (-0.1725)
4	0.0001 (0.1699)	0.0003 (0.4144)	0.0000 (0.0202)	-0.0002 (-0.2167)	-0.0002 (-0.1765)	-0.0001 (-0.0525)	0.0011 (0.8838)	-0.0003 (-0.1513)	-0.0006 (-0.3142)
5	0.0002 (0.3938)	-0.0001 (-0.1172)	-0.0003 (-0.3738)	-0.0002 (-0.3059)	-0.0001 (-0.1503)	0.0009 (0.9073)	0.0018 (1.3864)	-0.0010 (-0.6135)	-0.0005 (-0.2698)
6	-0.0002 (-0.5938)	-0.0004 (-0.7585)	-0.0004 (-0.6356)	-0.0003 (-0.3981)	0.0007 (0.7797)	0.0009 (0.9005)	0.0011 (0.8576)	-0.0010 (-0.6066)	-0.0008 (-0.4329)
7	-0.0002 (-0.4680)	-0.0002 (-0.3165)	-0.0001 (-0.0997)	0.0010 (1.1927)	0.0012 (1.2913)	0.0012 (1.3350)	0.0006 (0.4681)	-0.0005 (-0.3067)	-0.0019 (-1.0410)
8	0.0000 (0.0348)	0.0001 (0.2086)	0.0012 (1.6028)	0.0014 (1.5817)	0.0014* (1.7261)	0.0016* (1.8453)	0.0013 (1.0129)	-0.0004 (-0.2154)	-0.0012 (-0.6878)
9	0.0001 (0.2478)	0.0012* (1.8412)	0.0013* (1.6996)	0.0014* (1.9107)	0.0016** (2.0092)	0.0012 (1.4227)	0.0006 (0.4419)	-0.0004 (-0.2268)	-0.0017 (-1.0064)

Table 8. Continued

	1	2	3	4	5	6	12	18	24
10	0.0010** (2.2283)	0.0012* (1.8826)	0.0013** (2.0478)	0.0015** (2.1397)	0.0011 (1.3757)	0.0012 (1.3401)	-0.0002 (-0.1579)	-0.0006 (-0.3490)	-0.0018 (-0.9927)
11	0.0002 (0.4062)	0.0002 (0.4597)	0.0005 (0.7658)	0.0001 (0.0643)	0.0001 (0.1621)	0.0009 (0.9213)	-0.0019 (-1.4114)	-0.0014 (-0.8901)	-0.0020 (-1.0732)
12	0.0000 (0.1163)	0.0003 (0.5737)	-0.0001 (-0.2042)	-0.0001 (-0.0773)	0.0007 (0.7634)	0.0001 (0.1592)	-0.0019 (-1.5095)	-0.0017 (-1.1087)	-0.0018 (-0.9249)
13	0.0002 (0.6843)	-0.0002 (-0.3441)	-0.0001 (-0.1573)	0.0006 (0.8061)	0.0001 (0.1168)	-0.0006 (-0.6465)	-0.0017 (-1.2670)	-0.0031* (-1.9588)	-0.0017 (-0.8726)
14	-0.0004 (-0.7978)	-0.0003 (-0.5248)	0.0004 (0.5419)	-0.0001 (-0.1803)	-0.0009 (-0.9320)	-0.0003 (-0.3399)	-0.0020 (-1.4830)	-0.0029* (-1.8946)	-0.0016 (-0.8469)
15	0.0001 (0.1878)	0.0008 (1.2859)	0.0003 (0.3966)	-0.0004 (-0.4895)	0.0001 (0.1016)	-0.0006 (-0.5635)	-0.0016 (-1.1032)	-0.0029* (-1.8480)	-0.0006 (-0.3322)
16	0.0007* (1.6882)	0.0002 (0.3388)	-0.0005 (-0.6580)	0.0000 (0.0131)	-0.0007 (-0.7024)	-0.0014 (-1.2618)	-0.0018 (-1.2215)	-0.0030* (-1.7674)	0.0000 (0.0111)
17	-0.0005 (-1.1838)	-0.0012* (-1.7839)	-0.0007 (-0.8779)	-0.0014 (-1.5350)	-0.0021** (-1.9934)	-0.0028** (-2.4499)	-0.0023* (-1.6707)	-0.0029* (-1.6705)	-0.0005 (-0.2643)
18	-0.0007 (-1.3808)	-0.0002 (-0.2902)	-0.0009 (-1.1413)	-0.0016* (-1.6959)	-0.0023** (-2.2365)	-0.0021** (-2.0049)	-0.0019 (-1.3966)	-0.0019 (-1.1198)	0.0000 (0.0119)
19	0.0005 (1.3948)	-0.0002 (-0.3074)	-0.0009 (-1.1773)	-0.0016* (-1.8683)	-0.0014 (-1.5231)	-0.0011 (-1.1023)	-0.0025* (-1.9035)	-0.0010 (-0.6285)	0.0022 (1.2268)
20	-0.0007* (-1.8091)	-0.0014** (-2.3334)	-0.0021*** (-2.8748)	-0.0019** (-2.3517)	-0.0016* (-1.7558)	-0.0017* (-1.7249)	-0.0025* (-1.9588)	-0.0013 (-0.7651)	0.0021 (1.0887)
21	-0.0007 (-1.5716)	-0.0014** (-2.4469)	-0.0012* (-1.7697)	-0.0009 (-1.1387)	-0.0010 (-1.1632)	-0.0010 (-1.0721)	-0.0023* (-1.8310)	0.0000 (-0.0248)	0.0026 (1.3998)
22	-0.0007 (-1.6388)	-0.0005 (-0.9432)	-0.0002 (-0.3594)	-0.0003 (-0.3794)	-0.0003 (-0.3452)	-0.0004 (-0.3900)	-0.0016 (-1.0916)	0.0014 (0.8288)	0.0029 (1.4568)
23	0.0002 (0.5396)	0.0005 (0.8331)	0.0004 (0.6901)	0.0004 (0.6248)	0.0003 (0.4224)	0.0005 (0.6964)	-0.0001 (-0.0712)	0.0023 (1.5013)	0.0036* (1.9190)

This table contains the average cumulative returns and t-statistics in brackets from the 24 hours of the corresponding day up to different hourly holding times (1, 2, 3, 4, 5, 6, 12, 18 and 24) following the event over the whole sample. Significant coefficients are denoted by ***, ** and * for 1%, 5% and 10% significance levels, respectively.

Table 9. Sunday's post event holdings for each hour

	1	2	3	4	5	6	12	18	24
0	0.0003 (0.7594)	0.0002 (0.4357)	0.0002 (0.3733)	0.0001 (0.1766)	0.0003 (0.4357)	0.0002 (0.2467)	0.0002 (0.1319)	0.0021 (1.3365)	0.0031 (1.5487)
1	0.0000 (-0.0840)	0.0000 (-0.0558)	-0.0001 (-0.1627)	0.0001 (0.1077)	0.0000 (-0.0271)	-0.0014 (-1.2981)	0.0001 (0.0482)	0.0033* (1.9262)	0.0032 (1.4778)
2	0.0000 (0.0134)	-0.0001 (-0.1408)	0.0001 (0.1872)	0.0000 (0.0123)	-0.0013 (-1.3980)	-0.0008 (-0.8675)	0.0004 (0.2352)	0.0038** (2.0484)	0.0036* (1.6785)
3	-0.0001 (-0.1927)	0.0001 (0.2064)	0.0000 (0.0068)	-0.0013 (-1.5108)	-0.0008 (-0.9183)	-0.0014 (-1.2714)	0.0009 (0.6006)	0.0036* (1.9599)	0.0034 (1.6296)
4	0.0002 (0.4997)	0.0001 (0.1399)	-0.0012* (-1.6612)	-0.0008 (-0.9148)	-0.0013 (-1.2813)	-0.0012 (-1.0847)	0.0018 (1.1943)	0.0033* (1.7608)	0.0031 (1.4729)
5	-0.0001 (-0.2240)	-0.0014** (-2.1791)	-0.0010 (-1.3789)	-0.0015* (-1.6738)	-0.0014 (-1.4083)	-0.0006 (-0.5482)	0.0018 (1.2744)	0.0031* (1.7653)	0.0029 (1.3901)
6	-0.0013*** (-2.9290)	-0.0008 (-1.4282)	-0.0014* (-1.6720)	-0.0013 (-1.3547)	-0.0005 (-0.4614)	0.0000 (-0.0304)	0.0019 (1.3852)	0.0028 (1.6253)	0.0032 (1.5184)
7	0.0005 (1.0329)	0.0000 (-0.0544)	0.0000 (0.0193)	0.0008 (0.7684)	0.0013 (1.2124)	0.0014 (1.2889)	0.0047*** (3.2341)	0.0045** (2.4448)	0.0059*** (2.6980)
8	-0.0005 (-1.0805)	-0.0005 (-0.6708)	0.0003 (0.3604)	0.0008 (0.8620)	0.0010 (0.9588)	0.0012 (1.1125)	0.0046*** (3.1270)	0.0044** (2.4925)	0.0062*** (2.8123)
9	0.0001 (0.1243)	0.0008 (1.2086)	0.0013* (1.7151)	0.0015* (1.7450)	0.0017* (1.8445)	0.0023* (2.1632)	0.0050*** (3.5286)	0.0047*** (2.8162)	0.0060*** (2.6811)
10	0.0008 (1.4110)	0.0013* (1.8191)	0.0014* (1.8765)	0.0017* (1.9433)	0.0022** (2.1980)	0.0030*** (2.6209)	0.0045*** (3.1286)	0.0043** (2.5274)	0.0062*** (2.6832)
11	0.0005 (1.0334)	0.0006 (1.1339)	0.0009 (1.2385)	0.0015* (1.6705)	0.0022** (2.0934)	0.0024** (2.4274)	0.0037*** (2.7038)	0.0036** (1.9850)	0.0052** (2.2676)
12	0.0001 (0.3788)	0.0004 (0.6944)	0.0010 (1.2726)	0.0017* (1.7796)	0.0019** (2.0963)	0.0019** (2.0290)	0.0029** (2.0636)	0.0032* (1.7692)	0.0040* (1.7107)
13	0.0003 (0.5754)	0.0008 (1.2515)	0.0016* (1.7425)	0.0018** (1.9964)	0.0018* (1.9087)	0.0032*** (3.0004)	0.0031** (2.0815)	0.0045** (2.3445)	0.0043* (1.8439)
14	0.0006 (1.1412)	0.0013 (1.6293)	0.0015* (1.8352)	0.0015* (1.7751)	0.0030*** (2.9606)	0.0034*** (3.0444)	0.0032** (2.1461)	0.0050** (2.5134)	0.0042* (1.7201)
15	0.0008 (1.1241)	0.0010 (1.4159)	0.0010 (1.2741)	0.0024** (2.5711)	0.0028*** (2.6631)	0.0027** (2.4319)	0.0025* (1.6538)	0.0037* (1.8499)	0.0043* (1.8621)
16	0.0002 (0.3452)	0.0002 (0.2870)	0.0017* (1.7581)	0.0021* (1.8719)	0.0019* (1.6744)	0.0015 (1.2138)	0.0013 (0.7828)	0.0032 (1.4955)	0.0045* (1.8682)
17	0.0000 (-0.0065)	0.0014* (1.8262)	0.0019* (1.8791)	0.0017 (1.5965)	0.0013 (1.1210)	0.0013 (1.1322)	0.0012 (0.6883)	0.0028 (1.2896)	0.0039 (1.5960)
18	0.0014** (2.5144)	0.0019** (2.2711)	0.0017* (1.8417)	0.0013 (1.2537)	0.0013 (1.2830)	0.0010 (0.8488)	0.0013 (0.8032)	0.0021 (0.9550)	0.0049** (2.0565)

Table 9. Continued

	1	2	3	4	5	6	12	18	24
19	0.0004 (0.8143)	0.0003 (0.4268)	-0.0002 (-0.2377)	-0.0001 (-0.1780)	-0.0005 (-0.5784)	-0.0001 (-0.1258)	0.0013 (0.8044)	0.0011 (0.5312)	0.0034 (1.4170)
20	-0.0001 (-0.3761)	-0.0006 (-1.0904)	-0.0005 (-0.9451)	-0.0009 (-1.3129)	-0.0005 (-0.5900)	-0.0002 (-0.1956)	0.0016 (0.9903)	0.0008 (0.3736)	0.0025 (1.0372)
21	-0.0004 (-1.2355)	-0.0004 (-0.8820)	-0.0008 (-1.3191)	-0.0004 (-0.4986)	0.0000 (-0.0509)	-0.0002 (-0.2397)	0.0011 (0.6574)	0.0017 (0.8320)	0.0022 (0.9246)
22	0.0000 (0.1091)	-0.0003 (-0.6224)	0.0000 (0.0578)	0.0004 (0.4801)	0.0002 (0.2440)	-0.0002 (-0.1688)	0.0018 (1.0307)	0.0031 (1.5016)	0.0024 (0.9710)
23	-0.0004 (-0.9574)	0.0000 (0.0049)	0.0004 (0.4953)	0.0002 (0.2290)	-0.0002 (-0.2323)	-0.0001 (-0.1212)	0.0015 (0.8705)	0.0026 (1.2642)	0.0028 (1.0907)

This table contains the average cumulative returns and t-statistics in brackets from the 24 hours of the corresponding day up to different hourly holding times (1, 2, 3, 4, 5, 6, 12, 18 and 24) following the event over the whole sample. Significant coefficients are denoted by ***, ** and * for 1%, 5% and 10% significance levels, respectively.

Table 10. Percentages of significant returns using 1-year rolling window

	0	1	2	3	4	5	6	12	18	24
MONDAYS										
4	15.33	7.28	1.92	14.94	18.39	24.90	21.84	42.15	39.85	46.74
5	7.28	9.96	23.37	27.20	28.74	23.75	25.29	34.10	42.53	42.91
6	9.96	36.78	21.46	18.77	17.24	18.39	17.62	39.08	40.23	36.78
12	22.61	2.30	0.00	34.10	53.26	35.63	49.43	44.83	32.57	29.89
13	2.30	0.77	29.12	54.79	33.72	47.13	49.04	37.55	33.33	27.59
14	0.77	30.65	53.26	31.03	44.06	41.76	42.53	34.87	20.69	24.14
15	30.65	20.69	22.99	18.77	21.84	25.29	28.35	30.65	14.94	15.71
FRIDAYS										
0	12.26	7.66	25.29	34.10	37.16	33.72	32.57	30.65	42.91	49.04
1	7.66	31.42	41.00	39.08	34.87	25.67	42.53	26.82	51.34	49.04
2	31.42	12.64	11.49	16.48	9.96	26.82	26.44	18.77	47.89	47.89
15	10.73	33.33	48.66	59.00	62.07	59.39	59.77	54.02	44.83	46.74
16	33.33	24.90	46.36	60.92	50.57	51.72	35.25	43.68	36.02	31.03
17	24.90	28.74	44.44	36.02	33.72	19.16	27.97	29.50	18.01	18.01
18	28.74	20.69	22.61	20.69	8.43	16.09	10.73	24.90	13.79	9.58
SUNDAYS										
9	0.38	17.62	18.77	20.69	11.88	11.11	24.90	38.31	31.03	24.90
10	17.62	18.01	18.01	6.13	14.94	21.46	26.05	32.18	28.74	24.14
11	18.01	10.73	8.05	18.39	24.14	27.97	20.69	16.86	17.24	17.24

Table 10. Continued

	0	1	2	3	4	5	6	12	18	24
12	10.73	9.96	18.77	30.27	27.97	24.90	20.69	8.05	10.73	5.36
13	9.96	6.13	21.07	31.80	15.71	14.94	33.33	19.54	22.61	11.49
14	6.13	10.73	21.07	15.33	18.01	30.27	31.80	32.57	23.37	9.96
15	10.73	0.77	8.81	17.24	26.44	33.72	30.65	21.84	18.39	22.99

This table contains the percentages of mean returns, labelled as 0, and average cumulative returns up to different hourly holding times (1, 2, 3, 4, 5, 6, 12, 18 and 24) following the event over that are statistically significant over different rolling windows.

Table 11. Percentages of significant returns using 2-year rolling window

	0	1	2	3	4	5	6	12	18	24
MONDAY										
4	5.26	0.00	0.00	27.75	43.06	41.15	37.80	41.63	27.75	33.49
5	0.00	22.01	41.63	44.02	44.02	35.41	42.11	41.15	30.14	33.01
6	22.01	55.02	34.93	33.01	28.71	22.01	15.31	41.15	26.32	28.71
12	60.29	1.91	0.48	58.85	78.95	34.93	77.51	34.93	34.45	33.97
13	1.91	0.00	33.49	51.20	17.70	55.02	53.11	31.58	30.14	27.27
14	0.00	34.45	53.59	23.44	54.55	51.67	29.19	30.14	19.62	30.14
15	34.45	26.79	21.53	18.18	18.66	25.36	7.66	4.78	0.48	5.74
FRIDAYS										
0	9.09	8.13	33.97	46.41	44.02	41.63	40.19	60.29	65.07	66.51
1	8.13	32.06	56.94	43.06	40.67	35.89	47.85	50.72	69.86	67.94
2	32.06	32.54	24.40	26.32	13.40	33.49	30.14	40.67	66.51	72.73
15	10.05	55.98	70.33	70.33	92.82	92.82	81.82	94.26	68.90	63.16
16	55.98	54.07	56.46	67.94	70.81	59.81	49.28	55.50	45.45	42.58
17	54.07	2.87	19.14	29.19	26.79	17.22	22.01	29.19	18.18	27.75
18	2.87	49.28	28.71	34.93	8.61	22.01	17.22	46.89	20.10	9.57
SUNDAYS										
9	5.29	9.13	29.33	25.48	28.85	6.73	28.85	55.77	45.67	28.37
10	9.13	20.67	7.21	25.00	27.40	37.02	46.15	62.02	48.08	28.37
11	20.67	9.62	14.90	26.44	36.06	46.63	41.83	38.46	42.79	14.90
12	9.62	5.77	23.56	32.69	47.60	34.13	9.13	21.15	16.35	3.37
13	5.77	3.37	21.63	51.44	24.52	10.10	50.48	37.98	29.33	4.81
14	3.37	3.37	43.75	14.90	5.29	37.98	43.27	36.06	27.40	4.33
15	3.37	8.17	12.02	2.40	21.63	44.71	37.50	28.37	8.65	26.44

This table contains the percentages of mean returns, labelled as 0, and average cumulative returns up to different hourly holding times (1, 2, 3, 4, 5, 6, 12, 18 and 24) following the event over that are statistically significant over different rolling windows.

Table 12. Percentages of significant returns using 3-year rolling window

	0	1	2	3	4	5	6	12	18	24
MONDAY										
4	1.28	0.00	0.00	16.67	31.41	30.13	25.64	35.26	12.82	19.23
5	0.00	12.82	46.79	37.18	31.41	31.41	33.33	34.62	18.59	19.23
6	12.82	51.28	36.54	29.49	15.38	16.67	8.33	51.92	9.62	12.82
12	72.44	3.21	0.00	78.21	85.26	69.23	91.03	34.62	0.64	44.23
13	3.21	0.00	16.67	80.13	22.44	83.33	75.00	1.28	3.21	26.92
14	0.00	49.36	79.49	19.23	80.77	73.08	8.33	26.92	6.41	27.56
15	49.36	26.28	3.85	14.74	2.56	1.28	0.00	0.00	0.00	0.00
FRIDAYS										
0	10.19	9.55	35.03	64.97	60.51	36.94	36.94	83.44	81.53	84.71
1	9.55	17.83	98.73	71.34	31.21	31.21	65.61	58.60	96.18	93.63
2	17.83	42.04	39.49	25.48	22.93	38.85	30.57	49.04	91.08	96.82
15	15.92	60.51	78.34	87.90	100.00	100.00	100.00	100.00	100.00	100.00
16	60.51	71.34	91.72	100.00	100.00	100.00	97.45	80.89	89.81	69.43
17	71.34	14.65	77.07	89.17	73.89	31.21	78.98	51.59	56.69	39.49
18	14.65	99.36	97.45	62.42	15.29	51.59	31.21	68.79	45.22	14.01
SUNDAYS										
9	21.79	7.05	27.56	30.77	40.38	30.13	51.92	83.97	42.31	48.72
10	7.05	26.92	21.15	58.97	48.08	68.59	76.28	92.31	44.87	60.90
11	26.92	0.00	12.18	28.21	47.44	53.85	46.79	70.51	39.74	39.10
12	0.00	0.64	15.38	42.31	44.87	35.90	21.15	28.21	26.92	4.49
13	0.64	0.00	30.13	35.90	32.69	17.95	84.62	33.97	39.74	8.33
14	0.00	0.00	34.62	18.59	13.46	68.59	68.59	36.54	42.95	4.49
15	0.00	14.74	1.92	0.00	54.49	50.64	27.56	23.72	0.00	1.92

This table contains the percentages of mean returns, labelled as 0, and average cumulative returns up to different hourly holding times (1, 2, 3, 4, 5, 6, 12, 18 and 24) following the event over that are statistically significant over different rolling windows.

Figure 1. Bitcoin's hourly closing prices

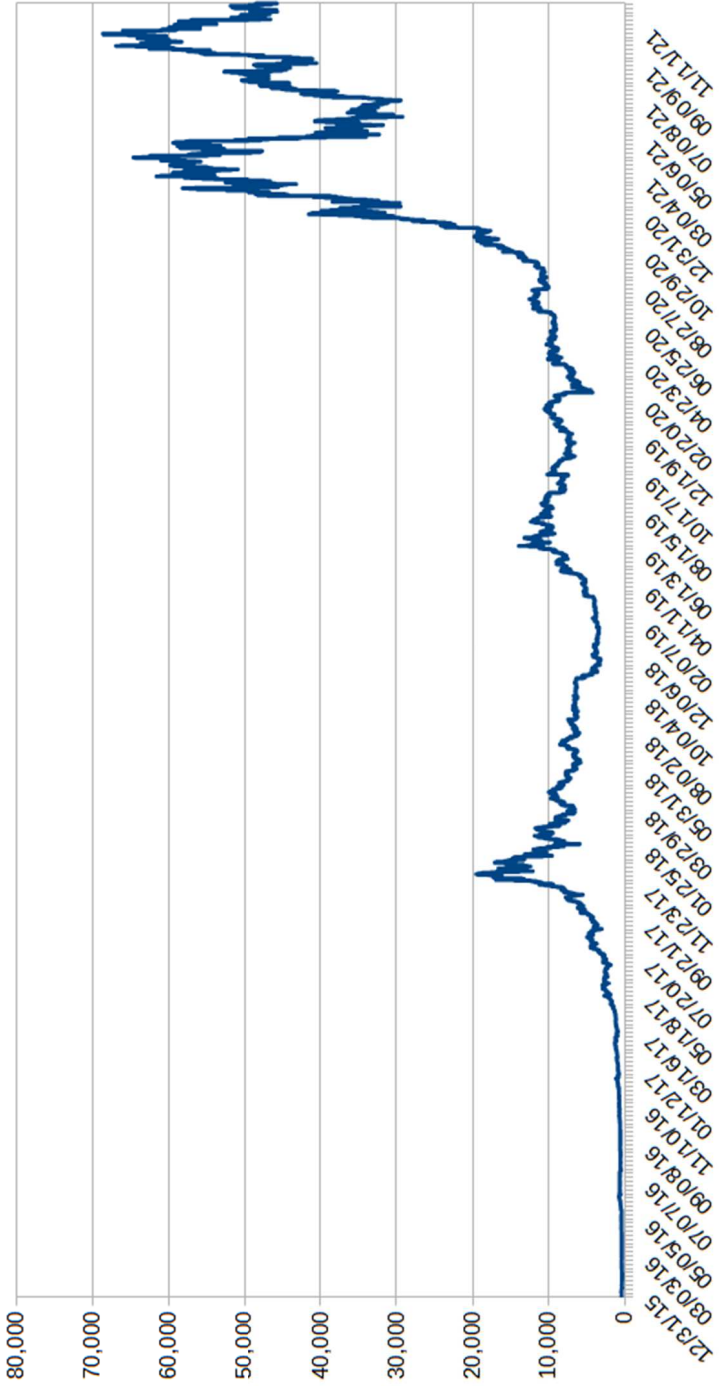


Figure 3. Z-stats of the proposed investment strategies

