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RESEARCH ARTICLE

On the Intraday Behavior of Bitcoin

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Abstract. We analyze the intraday time series of Bitcoin, comparing its features with those of traditional financial assets such as stocks and exchange rates. The results shed light on similarities as well as significant deviations from the standard patterns. In particular, our most interesting finding is the unusual presence of significant negative first-order autocorrelation of returns calculated on medium-frequency timeframes, such as one, two and four hours, signaling the presence of systematic mean reversion. It is also found that larger price movements lead to stronger reversals, in percentage terms. We finally point out the potential exploitability of the phenomenon by implementing a basic algorithmic trading strategy and retroactively applying it to the data. We explain the findings mainly through (i) investor and trader overreaction, (ii) excess volatility and (iii) cascading liquidations due to excessive use of leverage by market participants.

1. Introduction

Originating with the 2008 whitepaper by Satoshi Nakamoto,[1] cryptocurrencies can, in short, be defined as digital currencies in which encryption techniques are used to regulate the generation of units of currency and certify the transfer of funds without relying on any central authority. Although at first cryptocurrencies were considered by many to be a technological niche, they have progressively gained public relevance, and in recent years they have turned into a global phenomenon covered by mainstream media on a daily basis. The rise in popularity of cryptocurrencies coincided with a possibly even bigger increase in market value, accompanied by rather extreme volatility conditions. The spikes in price, together with the fact that in general—discounting cyclical expansions and contractions—crypto-assets have risen in value since their inception, made cryptocurrency appealing to the public from a speculative point of view. While crypto markets are likely incorporating a growing share of institutional investors as they evolve, it is reasonable to speculate that they include a fair share of non-professional agents as well.[2,3] This characteristic makes cryptocurrencies a rather unique niche in the financial asset ecosystem, one that becomes very interesting to study from a behavioral finance perspective. Behavioral finance distances itself from the presumption that financial markets always behave in accordance with the efficient market hypothesis, and that price changes always reflect available information. In a world in which there is a larger presence of ordinary investors and relatively little "smart money", one could expect to find evidence pointing towards the presence of inefficient and predictable price behavior. The efficiency and general characteristics of Bitcoin as a financial asset are of great interest, and have already been the subject of several studies, with mixed results[4–13] (see

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Corbet *et al.*[14] for an overview). Several studies focusing on the price of Bitcoin at the intraday level are also available. Scaillet *et al.* analyze the series in the period from 2011 to 2013, and find that jumps in price are frequent events, which cluster in time and have short-term positive impact on market activity and illiquidity.[15] Sensoy compares the time-varying weak-form efficiency of Bitcoin prices at a high-frequency level by using permutation entropy, and finds those markets to have become more informationally efficient at the intraday level since the beginning of 2016.[16] Aslan and Sensoy investigate the nexus between weak-form efficiency and intraday sampling frequency for the highest capitalized cryptocurrencies, providing evidence of major discrepancies on the predictability of cryptocurrency returns for alternative high frequency intervals.[17] Eross *et al.* examine intraday timeframes to reveal intraday stylized facts on the Bitcoin Market and study the intraday interaction between returns, volume, bid-ask spread and volatility.[18] Hu *et al.* investigate intraday price behavior of several cryptocurrencies, finding that trade prices cluster on round numbers throughout the day.[19] Bariviera *et al.* investigate some statistical properties of the Bitcoin market, comparing Bitcoin and standard currencies dynamics and focusing on the analysis of returns at different time scales.[20] Finally, Dyhrberg *et al.* find that the highest trading activity, highest volatility and lowest spreads coincide with US market trading hours, suggesting that most trades are non-algorithmic and executed by retail investors.[21]

The above cited studies come to different conclusions on Bitcoin's (in)efficiency, and a comprehensive understanding of intraday price and efficiency dynamics of cryptocurrencies is still lacking. The general scope of this article is therefore to provide an overview of the intraday behavior of Bitcoin price in the period from 2015 to 2018. The focus is on Bitcoin since, at the time of writing, it is and always has been by far the largest and most liquid digital crypto-asset on the market. More specifically, we contribute to the growing body of literature in two main ways. Firstly, given that the one at hand is still a relatively young market, it is important to understand whether or not recent behavior aligns with previous findings. We therefore analyze the series of Bitcoin price at the intraday level in the considered period, specifically focusing on outlining stylized facts. More precisely, we carry out an in-depth analysis of intraday returns of Bitcoin at both high- and medium-frequency timeframes, pointing out differences and similarities with traditional financial assets such as stocks and exchange rates. Those more conventional markets have been widely explored in this regard, and for them, broadly speaking, it is possible to identify a set of common empirical properties.[22–25] We here show how Bitcoin behaves similarly to traditional assets in several regards, albeit with some meaningful divergences. The second way in which this paper contributes is by focusing on the most striking of those divergences, namely the unusual presence of highly significant first-order negative autocorrelation of intraday medium-frequency returns. This phenomenon was, to the best of our knowledge, not previously documented for the Bitcoin market. It is common to observe significant negative autocorrelation in high-frequency return series of stocks and foreign exchange transaction prices, mainly due to the microstructure effect called bid-ask bounce.[26] In general, autocorrelation tends to disappear when considering returns calculated on larger intervals.[22,27] We show that this is not the case for Bitcoin, where negative autocorrelation of returns manifests itself at larger intraday timeframes, such as one, two and four hours. We dig deeper into this finding and go on to show, by means of a very simple trading strategy, the potential exploitability of this systematic intraday mean-regressing behavior. The positive association between intraday volatility and short-term price predictability is also highlighted. We believe the presented results to have important implications

for active players in the cryptocurrency space, and in particular for exchanges, market makers and traders, which might be able to take advantage of the described phenomena. This, in turn, could possibly speed up the road for Bitcoin towards a higher degree of market efficiency.

The rest of the paper is organized as follows. The next section provides an overview of the data that was used. Section 3 is dedicated to the analysis of the Bitcoin market and its intraday returns, highlighting similarities and differences with traditional financial markets and showing evidence pointing towards inefficiencies. Section 4 presents and discusses the existence of jumps in the Bitcoin price series, and shows how they increase the rate of predictability of price in the period immediately successive to them. Finally, the concluding section summarizes the main take-aways of this research, pointing out the limitations of our study and suggesting possible directions for further research.

2. Data

Our empirical study was performed using data from Bitstamp, one of the oldest and most liquid Bitcoin exchanges currently in activity. More specifically, the data we used was uploaded for free use to the Kaggle platform, an online community of data scientists and machine learners, by Mark Zielinski (Zielak).[28] The original series spans from 1 December 2012 to 27 June 2018, but for our analysis we only used data from 1 March 2015 onwards, since the first part of the series has a high amount of missing entries at the intraday level. In contrast, only a handful of one-minute timeframe data is missing in our sample period, therefore allowing for a complete examination of the intraday dynamics of Bitcoin. The original data matrix has one row for each minute, and the columns of the matrix are timestamp, opening price, closing price, high, low, and volume, with all prices being denominated in US dollars. The variable of interest for this study is price. We arbitrarily chose to use closing prices for our analysis, but the results would be exactly the same if we used the opening ones, as cryptocurrency markets operate 24/7, making the open of each time interval effectively equal to the close of the interval preceding it. In order to work with the data at different timeframes, the series was aggregated at various time intervals (five minutes, fifteen minutes and so on, up to a day) to obtain closing prices at the desired resolutions. The handful of missing data at the minute level were simply replaced with the previous data points.

3. Traditional Financial Markets and Bitcoin: A Comparison

As anticipated in the previous section, from the statistical analysis of financial asset returns it is, in general, possible to identify a set of common empirical properties.[22–25] Those properties are sometimes referred to as "stylized facts," and include heavy tailed distributions, gain/loss asymmetries, volatility clustering and absence of significant autocorrelation except for very small intraday time scales. The series of Bitcoin returns exhibits some of those usual characteristics, as well as some apparent anomalies. The scope of this section is to consider some of the stylized facts of traditional asset returns and show how they compare to what is happening in the Bitcoin markets at the intraday level.

3.1. Volatility—When thinking about Bitcoin as a financial asset, one of the first, if not the first word that comes to mind is "volatile." Let us first clarify what that actually means. Figure 1 plots the daily volatility index of the Bitcoin/Dollar exchange rate together with the
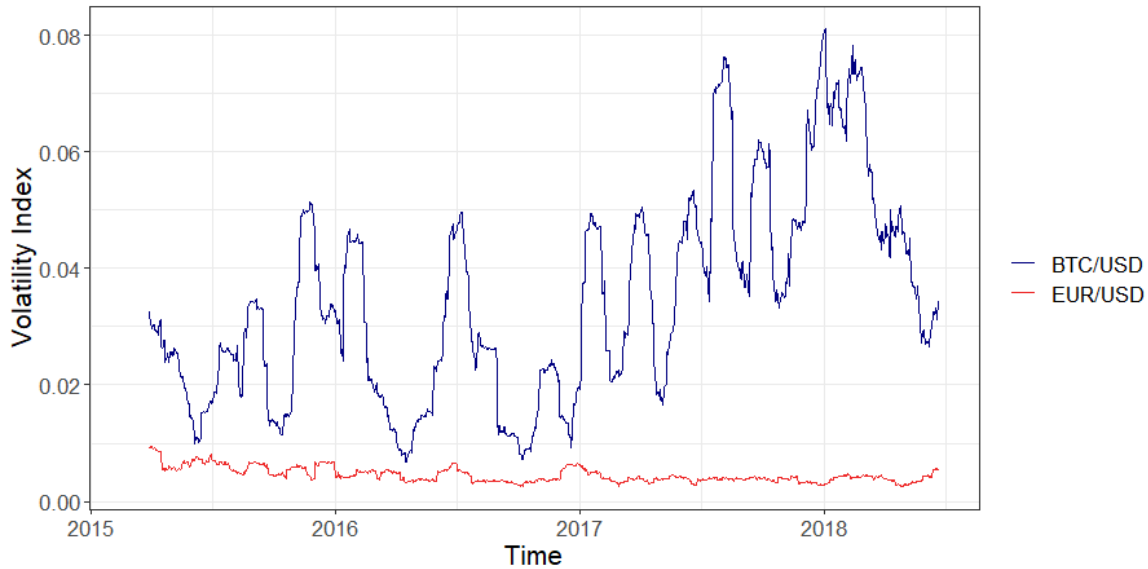
Fig. 1. Rolling 30-day volatility index calculated on the daily percentage returns of the Bit-coin/Dollar and Euro/Dollar rates of exchange.

one of the Euro/Dollar pair over our whole sample period. The index is a rolling estimate of the standard deviation of daily returns calculated over a period of 30 days, and the comparison shows how the volatility of Bitcoin is of a different order of magnitude than that of the Euro: the index of the cryptocurrency is on average approximately 10 times larger than the one of the legacy pair. Note that the Euro/Dollar pair is not a particularly stable one among other high-volume foreign exchange pairs. Another thing to note is that, while it may seem hard to believe, Bitcoin is the least volatile asset in the cryptocurrency class.[29] Looking at the matter from a behavioral standpoint, a very real case could be made for the presence of excessive volatility in the cryptocurrency markets. We believe that the extreme volatility conditions are in large part imputable to the fact that there is no "book" to base valuations on, and, because of this, price discovery is much more subject to news, events and, more in general, speculation. Even if it is beyond the scope of this study, we believe that an in-depth, evidence-based analysis on the matter could be a very interesting topic for new research. In this section we limit ourselves to the study of volatility conditions and to the observation of how they relate to other important measurable market quantities, such as volume.

Up to now we used a rolling index to visualize the overall daily volatility of the series. We now focus on intraday volatility, and use the standard deviation of hourly returns during each day to assess it. The resulting series therefore consists of one data point for each 24-hour period, with each data point measuring the dispersion of hourly returns during a single day. This measure, while being less smooth, create a series of estimates which are not interdependent by construction. This allows the estimation of volatility clustering through direct measures of autocorrelation, while at the same time facilitating the comparison with volume. Intraday hourly volatility is shown in Figure 2, where the dashed red line depicts a rolling average of the index over 30 days. The volatility of hourly returns looks quite clustered even at first glance, with periods of relatively low volatility and periods of high volatility. The peak, like we saw from the rolling daily index,
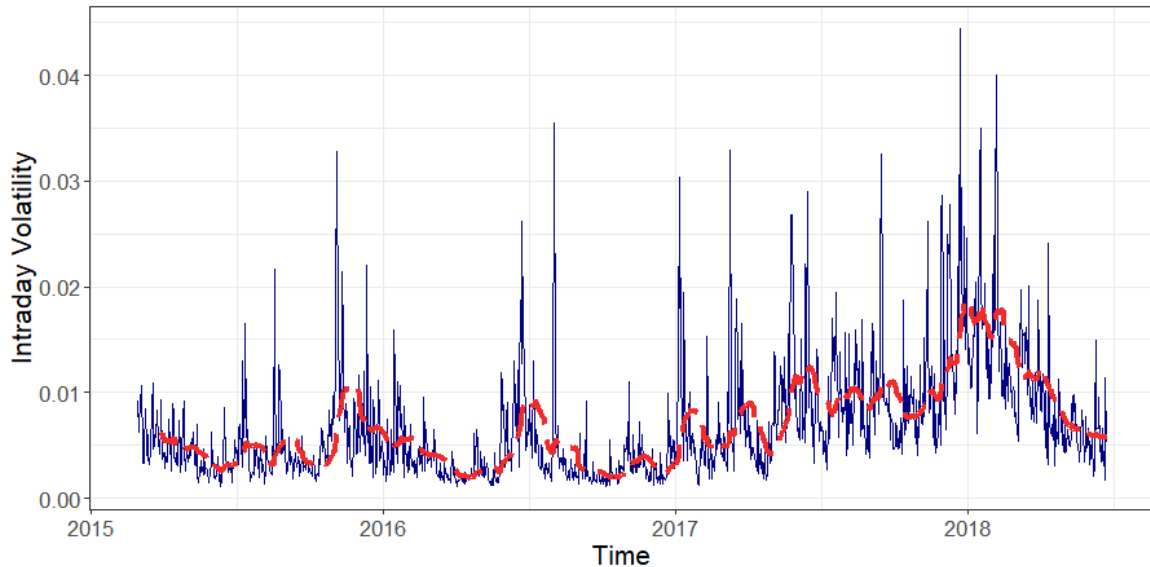
Fig. 2. Intraday hourly volatility index for Bitcoin returns (denominated in US dollars). Each point in the series represents the average volatility for the day. The dashed red line depicts the corresponding rolling 30-day average.

is found during the December 2017/January 2018 period, during which Bitcoin price reached its (then) all-time high before declining rapidly in the subsequent month.

Volatility clustering is a common occurrence both in the crypto markets and in traditional ones. It is well recognized that stock market returns contain little raw autocorrelation, in accordance with the efficient market theory.[30,31] This empirical fact does not, however, imply that returns are independent nor identically distributed. It is possible for the series to be serially uncorrelated but still dependent in other ways.[32] Figure 3 depicts the autocorrelation function for the intraday hourly volatility of Bitcoin calculated on the whole sample period. The confidence interval for the first-order autocorrelation coefficient, calculated at the 95% confidence level, spans from 0.66 to 0.72, showing high levels of temporal dependence. The autocorrelation function tends to slowly decline as the lag increases, but correlation remains significant up to a lag of 30 days and beyond. Note that we also applied this same technique to measure intra-hour volatility calculated over returns on five-minute periods, and results show that intra-hour volatility behaves very similarly to the hourly one.

Other, more common measures of volatility clustering include serial autocorrelation of squared and absolute returns. If those measures are significantly positive, there is evidence for the presence of volatility clustering. Measures of first order autocorrelation of squared and absolute autocorrelation of Bitcoin returns for different timeframes are shown in Table 1. Since all the coefficients are statistically significant, the p-values have not been included (the highest p-value is lower than 10^{-9}). These measures confirm earlier results, showing strong evidence of volatility clustering at all timeframes considered. It is also apparent that, barring the minute-by-minute case, autocorrelation of absolute returns is significantly larger than that of squared returns. This is consistent with the observations made by Ding et al.[32] All things considered, we can observe that, even if the volatility of returns in the Bitcoin market is considerably higher than that of
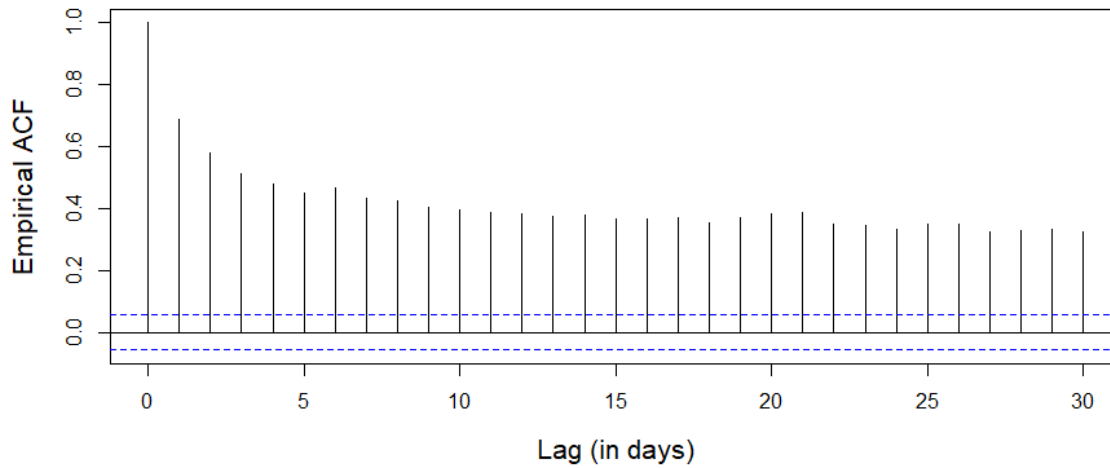
Fig. 3. Empirical autocorrelation function (ACF) for the intraday hourly volatility of Bitcoin returns. Lags are days.

Table 1. Basic measures of volatility clustering (all coefficients are significant at the 1% level).

Interval	Autocorrelation of squared returns	Autocorrelation of absolute returns
1 min.	0.3639	0.3459
5 min.	0.2592	0.3899
15 min.	0.2163	0.3812
30 min.	0.1748	0.3664
1 hour	0.1826	0.3369
2 hours	0.2086	0.3352
4 hours	0.1433	0.3194
1 day	0.1822	0.2428

legacy markets, the levels of volatility clustering present in the Bitcoin series approximately mirror those shown by stocks and foreign exchange pairs.

3.2. Volume—Trading volume plays a key role in the ecosystem of a market. Firstly, in absolute terms, it is indicative of the level of liquidity available on the market. Secondly, in relative terms, it is closely associated with volatility. In our case, there is also a third source of interest: the seasonal pattern in volume, or the absence thereof. These features are worth studying because they can aid us in understanding the composition of the population of Bitcoin market participants. Many traditional markets open and close at certain times, and trading can only take place in specific time windows that depend on geographic locations. Consequently, trading volume during hours in which markets are closed is zero. Differently from legacy ones, Bitcoin markets are open at all times, but if, hypothetically, Bitcoin trading were to be performed only by trading professionals and firms, volume would likely be concentrated in standard markets
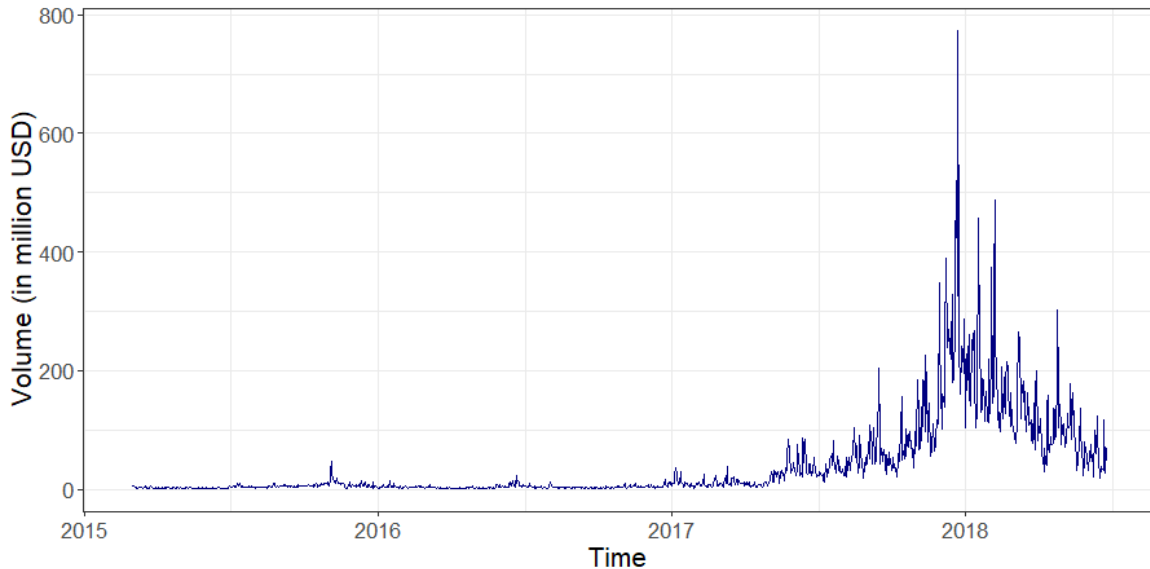
Fig. 4. Daily Bitcoin trading volume (in million US Dollars) on the Bitstamp exchange.

trading hours. In practice, we do not expect something that extreme, but we believe it would be plausible to find volume to be higher, to at least some extent, during standard market opening hours, because we do not expect the proportion of professionals participating in cryptocurrency trading to be zero.

Our analysis begins with an overview of volume over time. Figure 4 plots daily volume for the BTC/USD trading pair (in US dollars) on the Bitstamp exchange, considering the entire sample period. What stands out at a first glance is the expansion in volume that starts from the beginning of the second half of 2017 and sharply increases in intensity towards the end of the year, before the beginning of a slow decline in the first half of 2018. This path is similar to the trajectory that price had during the same period, and gives an indication of how high the interest in Bitcoin got when prices increased. The decline in 2018 is also something to take note of, because it shows that Bitcoin trading slowed down as price got lower.

The volume decline is closely linked to the decline in volatility. A large body of literature has focused on the role of traded volume in predicting movement in stock returns and volatility.[33] In the case of Bitcoin, correlation between daily volume and hourly intraday volatility is substantial, with the 95% confidence interval of the Pearson correlation coefficient being [0.66, 0.72]. The r^2 has a point estimation of 0.49, meaning that almost 50% of the variance in volatility can be explained by volume. The direction of the cause/effect relationship is unclear: once again, literature on the topic is quite rich. Balcilar *et al.* specifically address the relationship between volume and volatility for the Bitcoin market, using Bitstamp data for their study.[34] Intraday correlation between volume and volatility is a bit weaker than at the daily level, but still very strong, with the 95% confidence interval for the Pearson r between hourly volume and intra-hour five-minute volatility being [0.60, 0.61].

Let us now consider the seasonal components of volume. Figure 5 shows the estimates of the multiplicative seasonal coefficients for volume obtained using classical seasonal decomposition by moving averages. More specifically, the plotted estimates are obtained by decomposing the
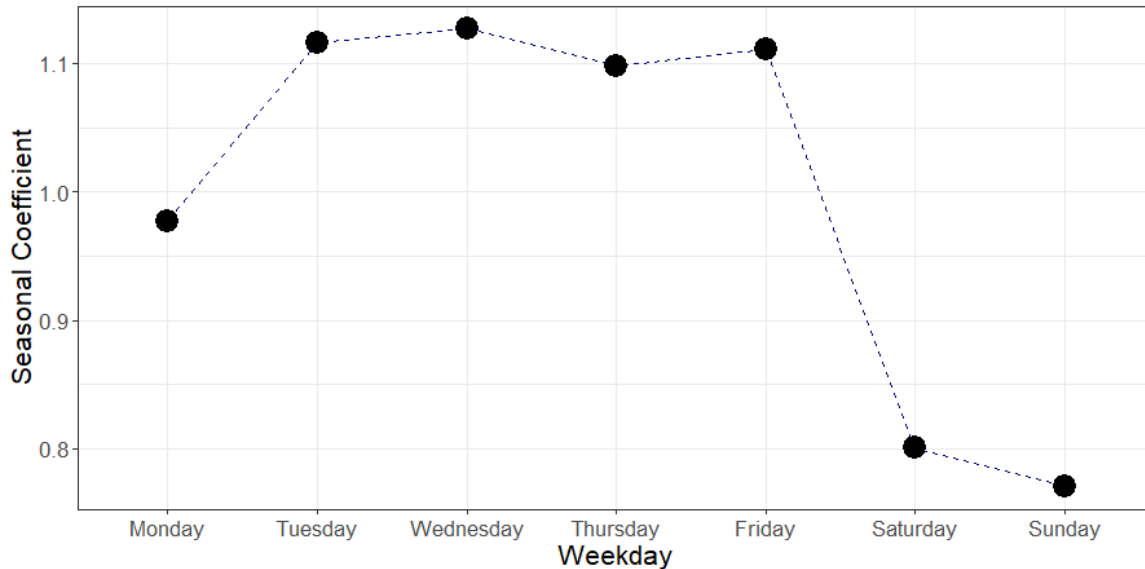
Fig. 5. Multiplicative seasonal coefficients for the daily trading volume on different weekdays.

series as $Y_t = T_t \cdot S_t \cdot \varepsilon_t$, where T is the trend, S is the seasonal component and ε is the error component (see *e.g.* Kendall and Stuart for more details).[35] Here the considered seasonal horizon is a week, thus the coefficients show the relative impact of different days of the week on Bitcoin trading volume. Volume on Saturdays and Sundays is on average approximately 20% lower than the average of the week, and approximately 30% lower than during other weekdays. This systematic difference between workdays and the weekend hints that Bitcoin trading is performed at least to some extent by trading firms and professionals. Of course, we cannot exclude other type of effects coming into play, but we can take this at least as an indication towards this direction, especially if we pair this piece of information with Figure 6, which shows the intraday seasonality pattern for Bitcoin volume (UTC times). The coefficients are calculated with the same technique used for the daily ones. Volume is considerably higher during the day than at night, with the intraday peak being located around the time in which both European and US markets are open (the New York Stock Exchange opens at 2.30 PM UTC), consistently with previous findings.[2,3] Low volume during night UTC hours is probably also influenced by the fact that most of Bitstamp clients are located in Europe and in the US, while Asian traders tend to prefer other, often local, alternatives. Trading hours in Europe and the Americas coincide with daylight in those continents, so it is likely that volume is higher in that window not only because markets are open, but also simply because more people are active during the day than at night. It is also important to note that we only worked with data from the Bitstamp exchange, which, although prominent, only accounts for a fraction of the total Bitcoin trading volume. Given this, future research may assess whether our results hold in the context of data originating from other leading Bitcoin exchanges.

3.3. Distribution of Returns—The non-Gaussian character of the distribution of returns of stocks and foreign exchange pairs has been repeatedly observed in various market data. One can summarize the empirical results by saying that the distribution of returns tends to be non-Gaussian, sharp-peaked and heavy-tailed, with these properties being more pronounced for intraday level
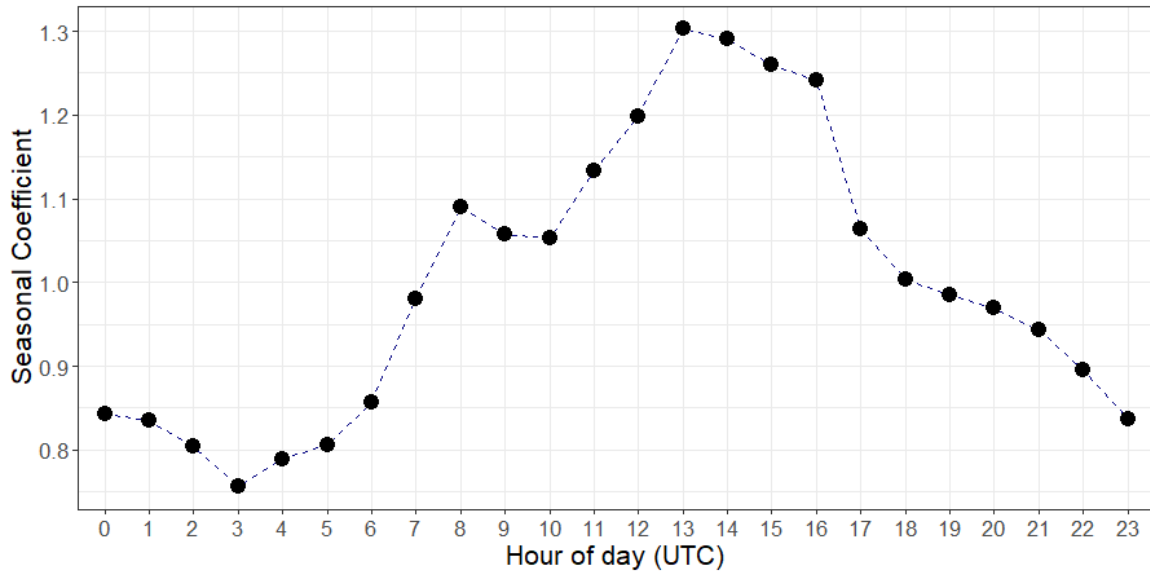
Fig. 6. Multiplicative seasonal coefficients for the hourly volume at different trading hours.

data.[22] The distribution of intraday Bitcoin returns also possesses those characteristics. Figure 7 shows, as an example, the kernel density of returns for the two-hour timeframe (in red), and a normal distribution with the same mean and standard deviation for comparison (in blue). The density shows a high concentration of probability towards the center and at the extremes of the distribution. Densities for other timeframes also possess similar characteristics, with higher frequency ones displaying more concentration towards the center of the distribution as well as heavier tails. The non-normal nature of intraday Bitcoin returns has been confirmed through use of the Jarque-Bera test, which test jointly for Kurtosis and Skewness (see *e.g.* Cromwell *et al.* for more details),[36] which returned highly significant p at all considered timeframes.

3.4. Gain/Loss Asymmetry—There is a tendency among financial time series for volatility to decline when returns increase and rise when returns decrease. This stylized fact was first discussed by Black and is traditionally known as "leverage effect," even though scholars have more recently argued that it may have little to do with actual leverage.[37,38] Although widely discussed in the economic and econometric literature, the leverage effect (or volatility-return correlation) has been less systematically investigated than the volatility clustering effect (volatility-volatility correlation). An important contribution to the subject has been given by Bouchaud *et al.*, who investigated the effect using stocks and stock indices returns.[39] We find that there is a significant correlation between volatility and returns in the Bitcoin market, as in traditional ones. Using the measure of intraday volatility previously described and daily returns, the point estimation for the Pearson correlation coefficient is -0.113, with the 95% confidence interval being $[-0.057, -0.168]$. At higher frequency, using the previously defined measure of intra-hour volatility for five-minute returns, the estimate for the correlation is similar (-0.117) but, given the higher sample size, it is accompanied by a smaller confidence interval of $[-0.106, -0.128]$. The statistically significant levels of negative correlation observed suggest that, as for stocks and foreign exchange markets, the volatility of Bitcoin tends to increase as price drops.

After observing that volatility tends to be higher when price is dropping, another question
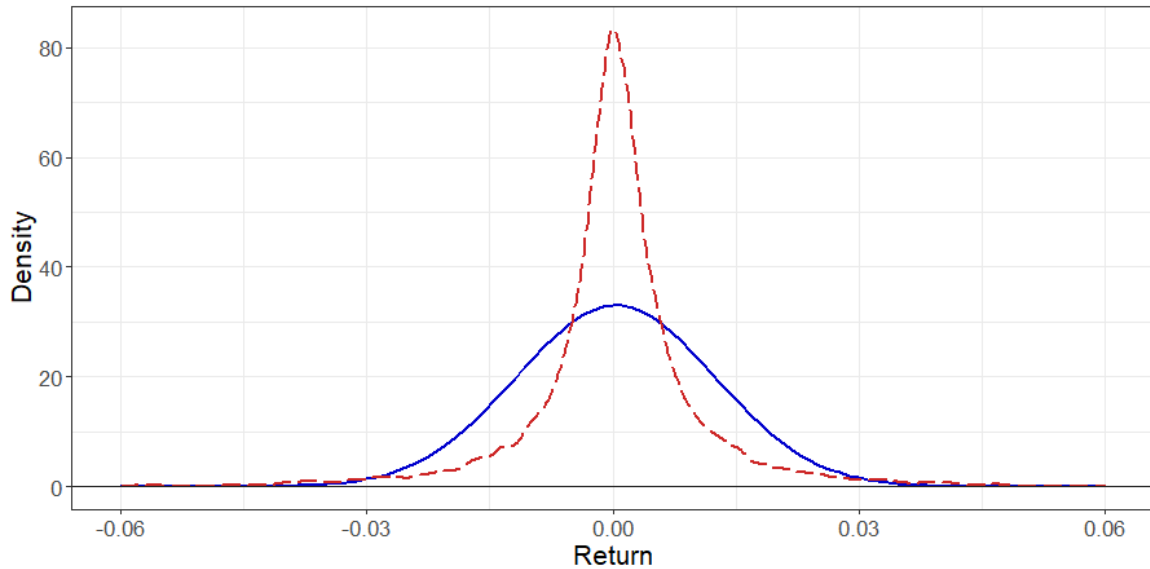
Fig. 7. Kernel density of Bitcoin two-hour returns (dotted red) compared with the probability density function of a normal distribution with the same mean and variance (solid blue).

Table 2. Average differences between positive and negative returns at different timeframes.

Interval	Average positive return	Average negative return	Difference	Relative difference	p-value
5 min.	0.176%	0.184%	0.008%	4,44%	$<10^{-16}$ ***
15 min.	0.268%	0.278%	0.010%	3,66%	5×10^{-6} ***
30 min.	0.363%	0.374%	0.011%	2,99%	0.0174 *
1 hour	0.499%	0.512%	0.013%	2,57%	0.1318
2 hours	0.699%	0.714%	0.015%	2.12%	0.3696
4 hours	0.972%	0.984%	0.012%	1.23%	0.6995
1 day	2.597%	2.497%	-0.100%	-3,93%	0.5628

naturally emerges. Is there an asymmetry between realized positive and negative Bitcoin returns at the intraday level? We try to answer the question by comparing the average of positive returns over the whole sample with the average of negative returns. The analysis is repeated for a variety of intraday timeframes, with the results being shown in Table 2. We observe that, at the 5-, 15- and 30-minute timeframes, negative returns are significantly larger (in absolute value) than positive ones. The difference is small, but large and consistent enough across high-frequency timeframes to be worthy of consideration. Differences become progressively smaller (in relative terms) and less significant at larger timeframes. The relationship even reverses at the daily level, showing larger average returns on the positive side than on the negative one. The decline in

significance is due in part to the smaller sample size, but the decrease in the relative value of the difference is likely due to the fact that Bitcoin had highly positive returns over the whole sample, and thus increasing the timeframe naturally generates larger positive returns. For this last reason, we believe high-frequency data to be much more relevant to the analysis in this context. Differences of this magnitude and significance at the intra-hour level are not the norm among foreign exchange data, in which asymmetries tend to be milder and often not even significant from a statistical point of view. We believe these levels of high frequency gain/loss asymmetry to be caused by a combination of investor overreaction, loss aversion effects, and high levels of volatility. These ideas will be explored more in depth in the upcoming section.

3.5. Autocorrelation of Returns—It is considered a well-known fact that price movements in liquid markets do not exhibit any significant autocorrelation. The reason for the absence of autocorrelation is intuitively easy to understand: if returns show systematic autocorrelation, that can be used to conceive and implement simple strategies to exploit it and net a positive expected return. These strategies, often referred to as statistical arbitrage, tend to "correct" visible inefficiencies of the market, effectively eliminating short-term predictability of returns. This does not apply to very small, high-frequency timeframes, which the markets use to react to information. High-frequency autocorrelation started to be well documented in the 90s, and has since become an established stylized fact.[27, 40, 41] The presence of negative autocorrelation at low timeframes is mostly attributed to market microstructure effects such as the bid-ask bounce, orderbook-related effects and the action of market makers, and is not easily exploitable. In general, the timeframe at which correlation is present is usually limited to a handful of minutes for organized futures markets, and even smaller for foreign exchange pairs,[22] while there is no evidence of any significant autocorrelation in liquid markets at medium-frequency timeframes, such as the hourly, four-hour or daily timeframes. The absence of autocorrelation does not hold systematically when the time scale is increased: weekly and monthly returns do sometimes exhibit significant levels of autocorrelation. Given that, however, the size of the sample is inversely proportional to the timeframe (if one considers larger intervals the sample size will naturally be lower), the statistical evidence regarding those low-frequency series is less conclusive and more variable across different samples.

With respect to this stylized fact, the behavior of Bitcoin returns deviates significantly from that of traditional financial assets. The data shows that autocorrelation of medium-frequency returns is far from absent, as shown from Table 3, which depicts the first-order autocorrelation coefficients of the series of Bitcoin returns at different timeframes, with the respective p-values. We observe significant negative Pearson correlation coefficients at all of the timeframes considered except for the daily one. For the lower time intervals (up to 15 minutes) we would expect some level of negative autocorrelation due, as explained before, to the bid-ask bounce and other microstructure-related effects. This type of autocorrelation is not easily exploitable, and does not constitute evidence against weak-form market efficiency.[42] The same cannot be said for the other timeframes: significant levels of negative autocorrelation found for returns calculated on intervals as wide as one, two and even four hours cannot usually be attributed to microstructural components of the market or orderbook effects. Significant levels of negative autocorrelation of returns imply systematic mean-reversion: a price move in any direction is, on average, followed by a slight move in the opposite direction.

It is important to note that we do not cover the specifics of the microstructure of Bitcoin

Table 3. First order autocorrelation coefficients at different timeframes.

Interval	Autocorrelation of returns	p-value
1 min.	-0.1445	$<10^{-200}$ ***
5 min.	-0.1016	$<10^{-200}$ ***
15 min.	-0.0575	6.08×10^{-86} ***
30 min.	-0.0440	2.16×10^{-26} ***
1 hour	-0.0557	1.86×10^{-21} ***
2 hours	-0.0858	3.20×10^{-25} ***
4 hours	-0.0564	1.46×10^{-6} ***
1 day	-0.0071	0.8047

markets in this paper. A study on such aspects of the markets would be very useful in order to check if and how much they are involved in the generation of the first-order anticorrelation effects at medium-frequency that we found. That said, if we assume microstructural components in this environment to be similar to the ones of traditional markets, the medium-frequency negative autocorrelation observed would not be attributable to those type of effects, and would imply partial predictability of returns that could be seen as evidence pointing towards the presence of weak-form market inefficiency.[30]

Estimated autocorrelation coefficients of order higher than one are statistically insignificant for returns computed at all timeframes considered, with occasional outliers that can be attributed to specific sample compositions. This suggests that the mean-reversion effect is limited to the period immediately subsequent to price movements, at all scales considered.

The presence of this medium-frequency first-order intraday autocorrelation does not have an immediate explanation, and is likely due to a combination of many different factors. We believe one of the most important of them to be investor and trader overreaction. The extreme volatility conditions, underlined in the related subsection, are also a clue in this direction: excess volatility is likely to be caused by non-rational behavior. In this sense negative autocorrelation of returns, which can here be seen as systematic mean-reversion, is causing volatility to be higher without any apparent fundamental reason. Another important factor towards the existence of negative autocorrelation of returns could be cascading liquidations. Many of the most liquid exchanges offer high leverage trading (up to $100x$ leverage), often without any margin maintenance costs. This, combined with the relatively low liquidity and extreme volatility that have characterized the crypto markets up to this point in time, can frequently lead to what we call *liquidation cascades*. When price moves violently in a direction, traders who are using high leverage will exhaust their margin, and their position will be liquidated (*i.e.* forcefully closed) by the exchange. This, in turn, will cause price to move further in the same direction, liquidating more traders, and so on. By the time this chain stops, the price is different from the equilibrium price of the asset; the market then quickly reverses to what participants consider to be a fair price. It is easy to see how this mechanism could create negative autocorrelation in the series of returns: violent movements

in a direction are followed, to at least some extent, by systematic regression towards the mean. The effect of liquidation cascades is also likely to be harshened by the fact that the quicker the price moves in a direction, the lighter the orderbook will be around market price. After a violent move, it will take some time for market participants to place orders. This will cause the cascade to play out even faster: if a position is forcefully closed at market while the orderbook is thin, the order will eat up the books and make price move more than it would have under normal circumstances. The role of liquidity is key in price determination, and especially so in a margin-trading environment with high volatility.[43] Since a very large portion of the Bitcoin trading volume comes from exchanges that offer leverage and margin trading on futures and perpetual swap contracts, the spot price will naturally follow and align to the price of these exchanges. The liquidation cascade effect itself can also be seen as a consequence of the non-rationality of market participants: it is hard to justify the use of high leverage in such extreme volatility conditions as rational behavior. We can thus argue that both this effect and traditional investor overreaction fall under the category of market inefficiencies.

4.   Jumps, Price Reversals and Predictability of Returns

4.1.   Price Jumps—Given what we observed in Section 3, and considering the clustered nature of volatility in this market, it would seem natural to expect the mean-regression effect to be larger after large price movements, and smaller in periods of lower volatility. The price history of Bitcoin is in fact characterized by the presence of very quick and large price movements that happen relatively frequently. In the finance literature, those type of movements are often referred to as *jumps*. Bitcoin is not the only asset that presents jumps in its time series: the price of stocks, commodities and foreign exchange pairs is often modeled as a jump-diffusion process, which is obtained by combining a Brownian Motion with drift (the continuous, diffusion component) and a compound Poisson process (the jump component). This is a type of process that sometimes jumps and has a continuous but random evolution between jump times.[44] We believe that the price of Bitcoin at the intraday level could also be appropriately modeled as a jump-diffusion process, as the exchange rate of the cryptocurrency with the dollar appears to evolve continuously, with the common occurrence of jumps at random times. Figure 8 shows an example of this behavior on an hourly chart displayed over a period of two weeks spanning between late April and early May of 2015.

The presence of proper jumps in the series can also be ascertained formally. There exist several statistical procedures to detect the presence of jumps in financial time series: we here opted for Jiang and Oomen's test, which uses "no jumps" as the null hypothesis.[45] The test returns significant p-values for all timeframes up to two hours, confirming that jumps are indeed present at every intraday scale.

4.2.   Jumps and Price Reversals—The modeling of the Bitcoin financial series is not the subject matter of this article, but the concept of jumps is a very useful one for our purposes. An important thing to note is that here we are not interested in formally defining what a jump is. Precisely defining how large a price movement should be to be considered a theoretically proper jump is a non-trivial problem to solve, and it is beyond the scope of this research. The goal of this section is to study how much large and quick price movements are contributing to the negative first-order autocorrelation of returns of the series found in the previous section. For this reason,
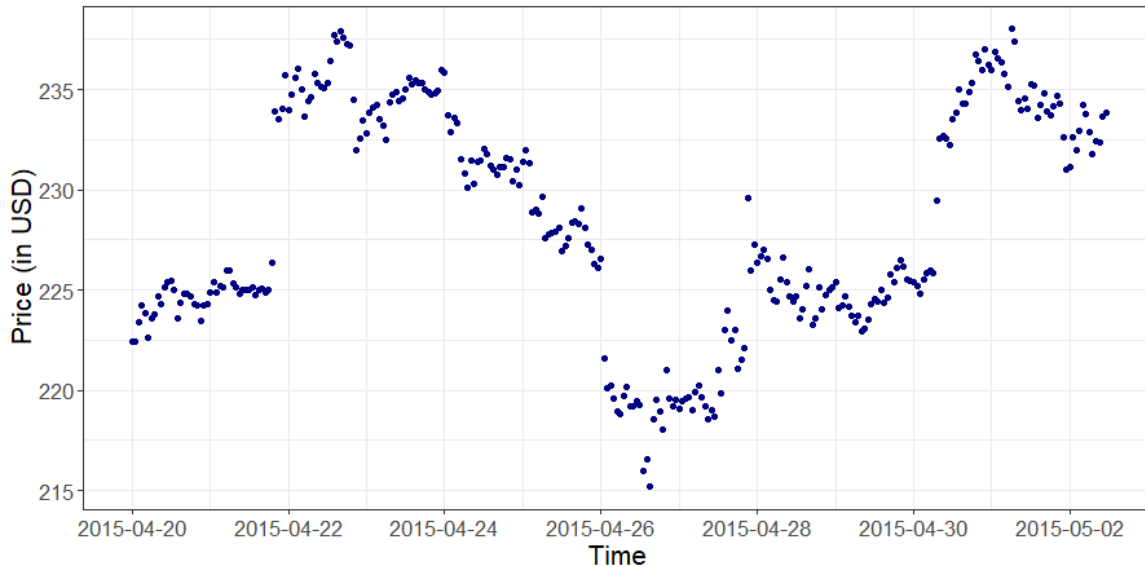
Fig. 8. Bitcoin hourly price (in US dollars) during a two-week period between late April and early May of 2015.

from now on we will use the word "jump" to refer to large price movements that happen in the span of one period, or, in other words, large single-period returns.

To understand the extent of the mean-reversion of price after movements of different sizes, we constructed a simple algorithm, which can be described through the four steps below:

(1) Choose the minimum size for a return to constitute a jump in price.
(2) Select all returns that constitute a jump according to the definition given in step 1 and store them in a vector.
(3) Fill another vector with returns calculated in the periods immediately successive to the jumps. This vector and the one constructed in step 2 will naturally have the same size.
(4) Plot both vectors in a scatterplot and calculate the correlation coefficient between them.

The resulting correlation coefficient allows us to obtain a measure of the sign and of the strength of the relationship between returns at times of large price movements and returns immediately successive to these movements. Another way of interpreting this is to consider the output as the first-order autocorrelation coefficient of the series of Bitcoin returns, calculated excluding returns that are smaller than the chosen threshold for jump size. The simple first-order autocorrelation coefficient of the series of returns can be obtained as a special case of the algorithm, setting the threshold for jumps at 0, which effectively means considering all returns in the computation, regardless of their size.

The algorithm described above was used to analyze the behavior of price after jumps of various size at all intraday timeframes, with the threshold for jumps depending on the timeframe. More specifically, we run the algorithm using an empirical set of thresholds that depended on the standard deviation of the series of returns under examination. For simplicity, we chose to use multiples of the standard deviation, so that the results are easy to understand and interpret. Table 4 summarizes the results of our analysis. The numbers in the cells are the correlation coefficients, sorted by timeframe (rows) and jump size (columns). As an example, the third element of the

Table 4. Correlation coefficients by timeframe (row) and size of jump (column).

	0	σ	2σ	3σ	4σ	5σ	6σ
1 min.	-0.1561	-0.2000	-0.1867	-0.1417	-0.1030	-0.0726	-0.0453
5 min.	-0.1027	-0.1232	-0.1272	-0.1574	-0.1705	-0.2099	-0.2186
15 min.	-0.0577	-0.0678	-0.0761	-0.0775	-0.0894	-0.1158	-0.1314
30 min.	-0.0441	-0.0519	-0.0436	-	-	-	-
1 hour	-0.0557	-0.0740	-0.0975	-0.1193	-0.1483	-0.1863	-
2 hours	-0.0858	-0.1294	-0.1648	-0.1946	-0.2314	-0.3308	-0.4010
4 hours	-0.0564	-0.0843	-0.1029	-	-0.0632	-	-

second row of the table contains the correlation between (a) the five-minute returns that are greater or equal (in absolute value) than twice the value of the standard deviation of the series of returns and (b) the returns of the five-minute long periods immediately successive to the jumps. Only statistically significant estimates are included. From the table it is immediately apparent how all significant coefficients are negative. This means that, whatever the volatility conditions, the tendency for price after movements in any direction is to revert and move in the opposite direction. It is also apparent that the coefficients for the one-minute and five-minute timeframes are relatively high. As noted before, this can mainly be attributed to market microstructure effects, and thus does not necessarily imply inefficiency or irrational behavior of market participants. The same cannot be said for coefficients calculated at larger time intervals: they too are highly significant at all timeframes, reaching particularly high levels when considering big jumps. This can be considered evidence for the presence of (partial) short-term predictability, and thus of inefficiency in the market. In particular, the higher coefficients across the board are those calculated at the two-hour timeframe. A graphical representation of the phenomenon for the two-hour timeframe is shown in Figure 9.

In general, correlation coefficients show a tendency to increase in unison with jump size. This does not apply to the one-minute timeframe, for which bid-ask bounce and market-making effects play a central role. The otherwise positive correlation between jump size and absolute correlation is coherent with the explanations of the phenomenon given in the previous section: the larger the price movement, the bigger the effect of overreaction and cascading liquidations should be, not only in absolute terms, but also in percentage ones. Bigger movements should cause larger liquidation cascades, and, if some investors have a tendency to overreact to market fluctuations, it would seem natural for the effect to be larger for larger price movements.

4.3. Exploiting Bitcoin's Inefficiency: An Algorithmic Approach—Focusing our attention on large jumps only, one can observe how coefficients for the hourly, bi-hourly and four-hour timeframes are exceptionally high. We would thus like to measure how much these levels of autocorrelation are empirically exploitable, assuming market microstructure to be similar to that of traditional financial markets. To test this, we constructed a very primitive trading strategy based on statistical arbitrage. We then retroactively applied it to the data to get an idea of its
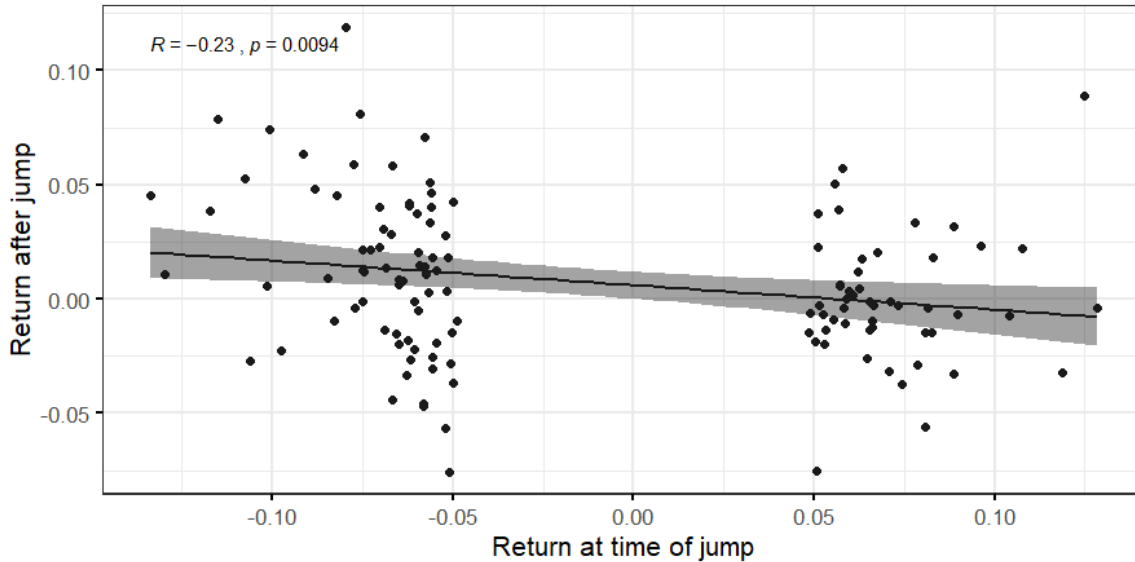
Fig. 9. Scatterplot of bi-hourly returns at and after jumps larger than or equal to 4σ.

profitability, calculating average per-trade profit and looking at performance over time, barring potential microstructural anomalies. The strategy is extremely simple: it bets on the market (goes long) if the last price movement was large and negative, and against the market (goes short) if the movement in the last period was large and positive. The trade is then closed after a single time unit has passed, depending on the timeframe. The strategy was applied to all intraday timeframes studied, and for each timeframe we used different cutoffs for the size of the move needed to trigger a trade. The maximum jump size used was equal to six standard deviations, since for jumps bigger than that the total number of jumps would be too small to obtain statistically significant results. The minimum threshold considered was zero, which implies that a trade happens at every time interval. Before moving forward, we believe it is important to note that both the time intervals on which returns are calculated and the thresholds for the size of the move needed to trigger a trade have been chosen in a completely arbitrary manner, without looking at the data. This was done to avoid various types of bias as well as overfitting.

Table 5 shows mean per-trade profitability for all timeframes and all jump sizes (without considering trading fees). As an example, the third element of the second row of the table contains the mean per-trade profitability of a strategy that checks price every five minutes, then goes long if the return in the last five minutes was negative and greater in absolute value than two standard deviations, or goes short if the return in the last five minutes was positive and greater than two standard deviations. Each trade is then closed after a single period, regardless of the outcome. In our example, this means that each trade only lasts five minutes. The results are significantly positive across the board, meaning that even with a basic strategy like the one used, the negative autocorrelation of returns would likely be exploitable, assuming market microstructure to be similar to that of legacy markets. It also appears that, on average, the bigger the jumps are, the higher the per-trade profitability is. Given the results on the correlation coefficients, this was to be expected. In this respect, the one-minute timeframe stands out as an exception, likely due to microstructural effects.

Table 5. Mean per-trade profitability of a basic mean-reverting strategy. Results are sorted by timeframe (row) and jump size needed to trigger a trade (column).

	0	σ	2σ	3σ	4σ	5σ	6σ
1 min.	0.02%	0.05%	0.07%	0.07%	0.06%	0.05%	0.02%
5 min.	0.02%	0.05%	0.07%	0.11%	0.14%	0.24%	0.30%
15 min.	0.02%	0.05%	0.07%	0.08%	0.12%	0.21%	0.28%
30 min.	0.02%	0.05%	0.04%	0.07%	0.13%	0.10%	0.12%
1 hour	0.03%	0.08%	0.15%	0.21%	0.34%	0.49%	0.58%
2 hours	0.05%	0.18%	0.30%	0.49%	0.74%	1.18%	1.81%
4 hours	0.05%	0.18%	0.32%	0.33%	0.18%	-0.17%	1.54%

The per-trade profitability not only goes up moving from left to right in the table, but also from top to bottom, meaning it also increases in unison with the magnitude of the time interval. For small timeframes per-trade profitability is low, and even though they would appear to still be the most profitable by compounding, the fees to be paid for the high number of trades and the bid-ask spread would likely lead the strategy to generate a net loss. The results on larger timeframes are instead much more interesting from an empirical point of view. They show relatively high per-trade profitability, with the highest and most consistent being the one on the two-hour timeframe. Large timeframes are also the ones in which microstructure is likely to play little to no effect on the dynamics of returns. We believe the pattern to be caused by a combination of different forms of irrational behavior, in the form of, as explained before, investor overreaction, excess volatility and overleveraging causing liquidation cascades.

Given that taker fees on some of the more prominent cryptocurrency exchanges are below 0.1% per trade, and given that liquidity should not be an issue when dealing with a relatively low trade frequency, it looks like the proposed strategy could even be viable in practice, barring microstructural anomalies. Figure 10 shows the performance of the strategy over time on the two-hour timeframe, without taking fees into account; the threshold to trigger a trade is set at zero, thus a trade gets executed every two hours. Initial capital is set at one unit, and the strategy does not compound the gains, meaning that the amount of capital used for each trade is always equal to one unit. Maintaining our usual assumptions, the strategy would have produced a significant return, multiplying initial capital by a factor greater than eight in a period of approximately three years. More importantly, the chart follows a stable path that resembles linearity, meaning that the profitability of the strategy is somewhat stable over time and across the whole sample, as opposed to being caused by some exceptional event.

In order to further evaluate our algorithmic approach on the two-hour timeframe as a measure of inefficiency, we additionally compared the proposed basic strategy with a naive, "purely random" strategy. The latter simply consists of drawing random numbers from a uniform distribution bounded between 0 and 1 at each time interval. The strategy then goes long if the generated number is greater or equal than 0.5, and short otherwise. We retroactively applied this
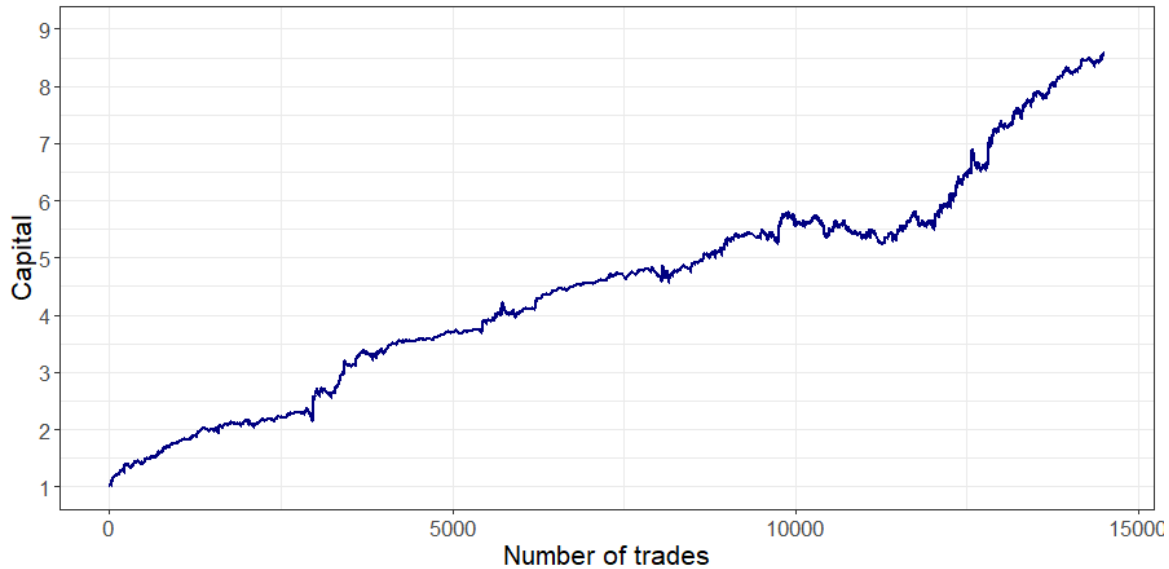
Fig. 10. Cumulative overall return of our basic statistical arbitrage strategy applied to the two-hour timeframe over the whole sample period. Trade size is fixed, meaning that gains are not compounded.

naive strategy to the series and repeated the process 10,000 times. Over those 10,000 trials the random strategy returned, on average, 0.99 units of capital (the initial quantity being 1), with a standard deviation of 1.44 units. While the fact that this random strategy gains or loses nothing on average is certainly not a surprise, the standard deviation is more interesting, as it confirms that the proposed algorithmic approach outperforms pure randomness not just by chance. This is also shown by the fact than none of the 10,000 random trials ended with final wealth greater or equal than 8.5, the number that was obtained through our proposed basic strategy. Note, additionally, that is very likely that there would be much better ways of profiting from the situation than the basic catch-all strategy we tried here. To construct the trading algorithm, we used arbitrary time intervals and jump sizes, based solely on practical convenience. Moreover, all parameters were kept fixed across the whole sample period, disregarding volatility conditions, as well as keeping the jump period and the subsequent one always equal and constant. Despite these constraints, returns at times of jumps in large intraday timeframes explain up to more than 5% of the return in the subsequent period. Adjusting the parameters of the algorithm and making them variable, *e.g.* as function of the volatility, could produce much better results in terms of variance explanation and, therefore, potential exploitability.

5. Discussion

We analyzed the intraday behavior of Bitcoin, comparing the features of its market with the stylized facts that characterize the series of traditional financial assets such as stocks and foreign exchange pairs. The comparison was based on data recorded between March 2015 and June 2018, and highlighted several similarities as well as some important differences. Among those differences, the primary finding was the presence of significant negative first-order autocorrelation in the series of Bitcoin returns, not only limited to extremely high-frequency returns, but extended

to medium-frequency ones, such as those computed at intervals of one, two and four hours. Negative autocorrelation of returns calculated at high-frequency timeframes such as one, five and fifteen minutes is not exclusive to the Bitcoin series, but is rather common among other assets and usually attributable to market microstructure, liquidity and orderbook-related effects such as the bid-ask bounce. As such, this type of autocorrelation does not *per se* constitute evidence for inefficiency. The same cannot be said about the negative autocorrelation found in the series of Bitcoin returns calculated at the one-, two- and four-hour timeframes. This type of autocorrelation is usually completely absent among returns of other assets. This phenomenon was, to the best of our knowledge, not previously documented in the existing Bitcoin literature, and its presence, barring anomalies in Bitcoin's market microstructure, constitutes serious evidence pointing towards intraday partial short-term predictability of the Bitcoin market.

Significant negative autocorrelation of returns indicates that price tends to systematically mean-revert in the period immediately subsequent to a move. We attribute this finding to a combination of factors. Among them, we believe the most important ones to be investor and trader overreaction, high volatility, and excessive use of leverage leading to liquidation cascades. We went on to show that the tendency for price to mean-revert after moving in a direction becomes bigger, in percentage terms, as the size of the price movement that precedes the reversal increases. This finding is in line with what we expected. To further highlight the potential exploitability of the negative autocorrelation at medium-frequency timeframes, we also constructed a very basic algorithmic trading strategy based on statistical arbitrage and retrospectively applied it to the data. Assuming the market microstructure of Bitcoin to be similar to the one of traditional financial markets, and thus its effect to be mostly limited to the returns calculated at high-frequency timeframes, the strategy resulted to be profitable, even after considering trading fees. While we believe that this inefficiency is likely to disappear as the Bitcoin market matures, we also believe the presented results to have important implications for active players in the cryptocurrency space, and in particular for exchanges, market makers and traders, who might be able to take advantage of the described phenomena. This, in turn, could possibly speed up the road for Bitcoin towards a higher degree of market efficiency.

Bitcoin is a very young asset, and the rapid growth and extreme volatility it has experienced since its inception in 2009 are truly remarkable. Given the volatile nature of the market and the peculiar characteristics of its participants, deviations from the dynamics of traditional financial assets are to be expected. Nonetheless, we did not anticipate such a significant degree of market inefficiency and predictability to be present at the intraday level. More research is certainly needed to confirm the results obtained in this study. First of all, our analysis does not take the development of the market over the time period between 2015 and 2018 into account. While we did not notice any macroscopic change in price behavior within our sample, more studies would be needed to confirm this, especially because of the changes in liquidity and market conditions following the massive expansion of crypto markets in 2017. It will also be very interesting to verify if the negative first-order autocorrelation of returns, and thus the tendency for price to reverse after movements in a direction, will persist over the years. Further research would also be needed to verify that the negative correlation of returns observed at medium-frequency timeframes is not caused by anomalies in the microstructure and the infrastructure of the Bitcoin market. For this purpose, we believe that an in-depth study on liquidity and on the composition and dynamics of the orderbooks of major Bitcoin exchanges would be of great relevance. Another

useful way of contributing to the research in this field would be to repeat the analysis with data coming from different exchanges. We believe that carrying out the analysis with intraday data coming from liquid exchanges that offer high leverage would be particularly useful, since it would allow us to directly test for the size and significance of the effect of cascading liquidations through a comparison with exchanges, such as Bitstamp, that do not offer leveraged trading.

Overall, we believe Bitcoin to be an extremely interesting financial asset to study, especially through the lens of behavioral finance. The unique composition of market participants makes it an ideal playing field to test hypotheses and study effects that would otherwise be difficult to isolate outside of a controlled environment. While the jury is still out on assessing the efficiency of Bitcoin, we hope our contribution will help in shedding more light on the matter. Given that studies in this field are still at a relatively early stage, we believe that research on the subject will have room to grow in the upcoming years.

Acknowledgments

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