Event-Driven Strategies in Crypto Assets

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1 Introduction

Due to structural, regulatory and security-related advantages, crypto assets attract an unparalleled attention all over the world and lead to a heated discussion whether crypto assets can be considered as a viable option for alternative investments. However, aside from regulatory uncertainty, a lack of profound academic studies and quantitative time series analysis seems to be a vast entry barrier for institutional investors, leading to the fact that the majority share of crypto assets are still being held by young, risk-tolerant retail investors with high affinity for blockchain technology and innovation.

This paper applies important findings of asset pricing theory on the rising academic field of crypto assets and deduces practical implications for retail and institutional investors. Our study includes descriptive statistics and correlation analysis of crypto and capital markets as well as an event and price impact analysis. Our empirical findings document no evidence for an increase of market efficiency of crypto assets as proxied by bitcoin and reveal significant inefficiencies, leaving valid arguments for either passive or active investment strategies. In addition, our event study findings show significant evidence for insider trading which should call market regulators for actions to fight lax regulations and ensure a fair market environment.

2 Performance and Diversification Potential

Globally, an increasing number of investors are evaluating the potential of crypto assets as an alternative investment. With this study we seek to provide evidence to what extent this new asset class can benefit the needs of institutional and retail investors.

With the crypto market peaking at over $800 billion at the beginning of January 2018, surging up from around $17.7 billion in early 2017, this infant and primarily illiquid market suffers from high volatility. This is clearly shown by the current market capitalization which has fallen by roughly 70% to $250 billion in July 2018. Despite the strong volatility associated with crypto assets in comparison to traditional asset classes, it is crucial to disentangle facts from perceptions.

We show that crypto assets can be used as a viable investment alternative by evaluating their potential merits with tried and tested econometric and financial models for risk and performance analysis. The research setting is structured as follows: Section 2 conducts a time series analysis with the largest and most renowned crypto currency bitcoin and a custom-weighted MSCI World index.[1] We test for correlation between both time series and determine whether any relationship is present. In section 3, we conduct an event study investigating the price impact of both positive and negative media coverage and forks.[2] In section 4, we evaluate the presence of arbitrage opportunities by analyzing the bitcoin price differential on two major crypto asset exchange plat-forms. In section 5, we briefly discuss the practical implications for retail and institutional investors.

[1] Detailed explanations follow in section 2.

[2] Detailed explanations follow in section 3.

2.1 Descriptive Time Series Analysis

The time series data with regards to the historical daily closing prices of bitcoin is retrieved from the open-source content distribution platform CryptoCompare using their API.[3] The time series reaches back until July 17th, 2010 and hence provides us with a substantial track record of historical closing prices to ensure valid statistical parameters.[4]

A standard assumption in time series analysis is the precondition that the underlying data set meets the requirements of stationarity. Stationarity implies a mean, variance and autocorrelation which remain constant over any period. To ensure that these properties are met, we transform the underlying data set by calculating the logarithm of the daily returns. In addition, log-returns follow a standard normal distribution so that statistical inferences are robust to statistical biases. The daily log-returns are calculated with the following formula:[5]

$$Y_t = \log(S_t) - \log(S_{t-1}) \tag{1}$$

which is equal to:

$$Y_t = log\left(\frac{S_t}{S_{t-1}}\right) \tag{2}$$

where: $\mathrm{S_t}$= current price at time t, S_t = current price at time t – 1.

Due to the MSCI World index being a traditional and commonly employed benchmark, it is used as a suitable proxy for equity stocks. Subsequently, we treat the daily log-returns of the MSCI World time series as an adequate benchmark for the daily log-returns of the bitcoin time series. The daily returns of the MSCI World index are transformed in the same fashion to ensure comparability. In addition, we build a custom MSCI World index as a consistent benchmark to account for varying proportions of crypto investment holdings.

To represent an appropriate and measurable benchmark we reweigh the MSCI sub-indices according to the geographic distribution of crypto assets around the word. That is, the balanced constituents of the benchmark are based on the MSCI Asia-Pacific, MSCI Europe, MSCI Latin America and MSCI North America.[6] Because there is no comparable MSCI index for Africa and the Middle East and the geographic proportion of the bitcoin distribution is marginally low, Africa is excluded from our custom benchmark. Since stock markets are closed on weekends and bank holidays, the bitcoin time series needs to be adjusted accordingly. As bitcoins can be traded every day of the year, respective

[3] Please refer to www.cryptocompare.com.

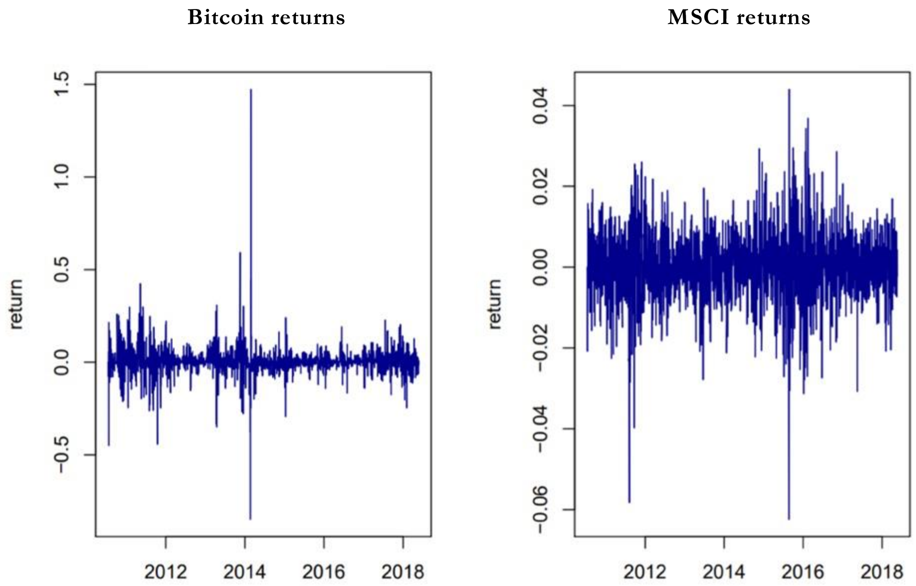
[4] The daily historical data are based on 00:00 GMT time according to CryptoCompare.

[5] Chorro et al. (2015).

[6] Hilemann and Rauchs (2017).

observations are dropped from the bitcoin sample to synchronize the two underlying time series. The historical log-return charts of bitcoin and the custom MSCI World index are plotted in Figure 1. The historical log-returns of bitcoin significantly outperform the historical log-returns of the MSCI World benchmark. However, the most striking observation regarding bitcoin is a negative return of –84.87% on February 20th, 2014, which is caused by a single sell order of roughly 6,000 bitcoins significantly below market price. The largest positive daily anomaly is associated with a return of +147.44% on February 26th, 2014, which is triggered by the collapse of "Mt. Gox", the world's largest crypto asset exchange at the time.

Figure 1: Log return plot of Bitcoin and custom MSCI World index.



In addition, Figure 1 illustrates that both time series move in clustered patterns. This statistical phenomenon is referred to as volatility clustering. Mandelbrot (1963) documents that "large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes."[7] As seen in both graphics, these clusters appear to come in bulks. Exogenous market shocks trigger erratic volatility peaks which disappear over an unpredictable period.[8] Hence, volatility clustering deviates from the classic random walk hypothesis as advocated by Malkiel (1973) where volatility remains constant over time. However, the volatility clustering obviously implies that asset volatility rather follows a mean-reversion and non-constant pattern de-pending the realization of past (lagged) prices. This accelerates the growing debate about volatility managed portfolios.[9]

[7] Mandelbrot (1963).

[8] Chorro et al. (2015).

[9] Moreira and Muir (2017).

Table 1 presents some selected summary statistics on the bitcoin and custom MSCI World time series returns. The mean log-return of bitcoin is +0.005772 whereas the mean log-return of the MSCI World index equals +0.0002385. Given the fact that the mean is most likely driven by outliers, it is more representative to look at the median statistics. The bitcoin median log-return equals +0.002214, whereas the median log-return of the MSCI World benchmark is +0.0005270. Subsequently, the bitcoin log-returns outperform the custom MSCI log-returns by a wide margin, which is also reflected in the higher standard deviation. Basically, standard deviation measures the width or dispersion of a return distribution and is usually used for return predictions. However, if returns deviate from a normal distribution, then skewness and kurtosis are arguably superior and more adequate measures to assess the risk of an investment compared to standard deviation.

Table 1: Descriptive summary statistics of Bitcoin and custom MSCI World index.

	Bitcoin	MSCI World
Min.	–0.8487650	–0.0624080
1st Quantile	–0.0145230	–0.0044192
Median	+0.0022140	+0.0005270
3rd Quantile	+0.0264370	+0.0052809
Max.	+1.4743950	+0.0440551
Mean	+0.0057720	+0.0002385
Std. Deviation	+0.0624615	+0.0088089
Skewness	+2.8191030	–0.4192669
Kurtosis	+76.209610	+3.5190380

Skewness measures the degree of asymmetry of a distribution around its mean and whether the curve leans to the left of right. A normal distribution of returns assumes skewness of 0 and is symmetrically distributed on both sides of the tails. If a distribution exhibits positive skewness, data concentrates more on the left side of the curve and the tail points right toward more positive values. Positively skewed investments exhibit a high frequency of small losses and few large gains. For negative skewness, data concentrates more on the right side and the tail points left towards more negative values. Negatively skewed investments exhibit a high frequency of small gains and few large losses. Based on our sample, the bitcoin return distribution is positively skewed to the right (skewness of +2.819193), whereas the custom MSCI World index return distribution is negatively skewed to the left (skewness of –0.4192669).[10]

[10] Franke and Huerdle (2004).

Kurtosis measures the degree of "peakness" of a distribution and indicates to what extend extreme events occur in the tails of the curve. A kurtosis of 3 is indicative of a standard normal (mesokurtic) distribution. A kurtosis exceeding 3 indicates a higher peaked distribution with fat tails. That is, the distribution is more concentrated around the mean but also exhibits a higher frequency of outcomes at the extreme ends of the curve. As a result, in fat tailed distributions the occurrence of extreme values of either sign is more likely to happen. In the underlying sample, kurtosis is primarily driven by outliers in the return distribution. Both time series show signs of peaked distributions which is characteristic of financial markets. However, bitcoin log-returns exhibit a much higher kurtosis (+76.20961) than the MSCI World log-returns (+3.519038), indicating that the bitcoin return distribution is highly leptokurtic and exhibiting longer tails relative to the custom benchmark.

Figure 2: Return distribution of Bitcoin and custom MSCI World index.

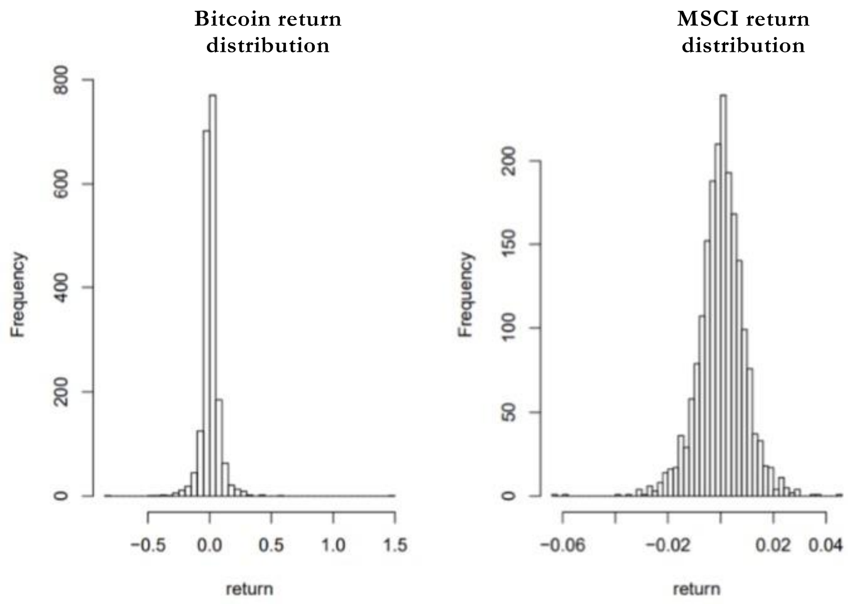


Figure 2 as well as the analysis of the measures of central tendency show that the bitcoin return as well as the MSCI return distributions do not follow a standard normal distribution. To verify this empirically, we formulate the Shapiro-Wilk (W-) test with the following hypotheses setting:

H_0: sample is normally distributed **H_1:** sample is not normally distributed

and compute following test statistic:[11]

$$W = \frac{\left(\sum_{i=1}^{n} a_i y_i\right)^2}{\left(\sum_{i=n}^{n}(y_i-\bar{y})\right)^2} \tag{3}$$

[11] Shapiro and Wilk (1965).

For ease of exposition, only the W-statistics are reported with the respective p-values in parentheses. Accordingly, we calculate a W-statistic of +0.71886 (2.2e−16) for the bitcoin log-returns and +0.96895 (2.2e−16) for the custom MSCI World benchmark log-returns. The reported W-statistics are statistically significant at the one percent level, meaning that the null hypothesis H0 can be rejected for both time series. As a matter of fact, both return distributions deviate from a standard normal distribution, leaving severe concerns about the applicability of the traditional random walk hypothesis and the use of conventional econometric concepts.

2.2 Correlation analysis

To analyze whether crypto assets serve as a reasonable complement to classic investment portfolios, their underlying correlations are of exceptional importance. Correlation determines the statistical strength and direction of the relationship between two variables. With perfect positive correlation (+1), asset prices move in tandem. Contrary, with perfect negative correlation (-1) prices move in opposite direction. In portfolio theory, researchers agree on the long-term benefits of stock returns over bonds and other asset classes.[12] However, in terms of tail events, uncorrelated assets can significantly increase risk-adjusted returns with the adequate portfolio rebalancing strategies.

The "Pearson r" correlation coefficient is one of the most heavily used correlation statistics to compute the degree of linear relationship between two variables. As demonstrated in the previous chapter, both time series data deviate from a standard normal distribution with a non-constant mean-reverting variance over time. Therefore, the Pearson correlation coefficient is not suitable for the underlying time series analysis since the bitcoin as well as the custom MSCI returns appear to be neither normally distributed nor homoscedastic.

More adequate measures of correlation are the Kendall's tau rank correlation and the Spearman's (rho) rank correlation coefficient. Both statistics represent non-parametric tests which measure the strength of the linear relationship between two individual time series based on the ranks of the underlying data. The time series observations are ordered and numbered accordingly. Both rank statistics do not require any specific assumptions on the distributions of the tested time series returns and must be, at minimum, ordinal in scale. In most situations both non-parametric correlation statistics will result in similar inferences. For ease of exposition only the Kendall's τ and Spearman's ϱ statistic are reported. Accordingly, calculations return a Kendall's τ -statistic of +0.0125849 and Spearman's ϱ statistic of +0.01909588. Both correlation coefficients demonstrate that the co-movement of bitcoin and MSCI returns are nearly zero. A weak correlation coefficient indicates that there is viable diversification potential from adding crypto assets into a classic stock/bond portfolio. Hence, market swings for one asset will not affect the other asset in the exact same way, and potential losses can be balanced by offsetting positions in different asset classes.

[12] Mehra and Prescott (1985).

However, the presence of the observed Spearman and Kendall correlation coefficients between equity stocks and crypto assets are not surprising and can be fully explained by their different return and risk patterns, as shown in section one. To access the real benefits of adding crypto assets to classic investment portfolios, further research about tail correlations is necessary. In the light of increasing dependency of different asset classes in times of financial turmoil it is crucial to comprehend the dynamics in the tails of the return distributions under extreme circumstances.

We recommend a left and right tail risk correlation forecast using auto-regressive methods chosen based on the degree of randomness embedded in both time series (auto-correlations).[13] Future research should test for stationarity and develop a GARCH model to predict future volatility movements and to measure tail-based dependency of traditional asset classes with crypto assets.

3 Event and Price Impact Analysis

After assessing the general efficacy of crypto assets as a viable and profitable alternative investment vehicle, we empirically address the research question whether considering crypto assets for investment purposes is a better fit for active or passive management strategies.

Fundamental to portfolio theory, Fama's (1970) efficient market hypothesis (EMH) is at the heart of modern portfolio strategies.[14] Efficient capital markets are based on the proposition of rational expectations and asset prices theoretically follow a random walk. The simple random walk is defined as a stochastic or random process where the current value of an asset reflects its past value plus an error term, with a mean value equal to 0 and a variance equal to 1. In fact, it can be shown that the stochastic process deviates from the simplistic assumptions. Hence, the random walk is a nonstationary process. The issue of nonstationary has been discussed in the previous section. This section deals with assessing the efficiency of crypto markets and how well new information is incorporated into the pricing of crypto assets. Given the fact that the infant crypto assets market remains largely unregulated, we can assume that prices are substantially driven by insider trading. However, to draw an informative conclusion, it is necessary to comprehend the level of efficiency that is prevalent in crypto markets.

The logic of Fama's (1970) efficient market hypothesis is intuitive. In theory, asset prices of to-morrow are not correlated with today's prices and thus will be primarily driven by tomorrow's news. Accordingly, future news and price movements are not predictable, as new information is quickly reflected in current asset prices. If this is the case, active management should not add value persistently and generate abnormal high returns. In correspondence with Sharpe's classical concept of market arithmetic, active management is a zero-sum game on aggregate, because the average active investor cannot outperform the efficient market consistently net of costs. The distribution of new information is channeled through various sources based on three distinctive forms of market efficiency.

[13] Box and Jenkins (2008).

[14] Fama (1970).

Depending on the coverage of information reflected in the current asset prices, we distinguish between weak, semi-strong and strong form of market efficiency.

To assess whether active or passive investment strategies should be applied with respect to crypto assets, we conduct an event study approach to investigate if and at what speed new information is reflected in current market prices. Regarding the increasing popularity of social media in the distribution of (crypto asset related) financial information and the high degree of homogeneity regarding the profile of today's digitally minded crypto investors, we assume that prices should adjust to material information immediately once disseminated over various channels.

Our event study methodology assumes that markets are at least semi-strong efficient. This implies that observed market prices already reflect all historical and publicly available information. As a result, new information that is yet unknown to the public should cause an immediate price reaction in either direction once disseminated.[15] We strictly follow a 9-step procedure as proclaimed by Andres et al. (2014) in conducting our short-term event study:[16]

(1) We define the exact event.
(2) We define the sample and news sources.
(3) We identify the exact event dates.
(4) We drop cofounding events.
(5) We compose the event list and retrieve asset price data.
(6) We determine the estimation method for expected return calculation.
(7) We determine the estimation and event windows.
(8) We calculate cumulative average abnormal returns (CAARs).
(9) We test for statistical significance.

With a hand-collected data set of positive and negative information events, we investigate whether bitcoin prices as a proxy for crypto assets is influenced by media coverage. Our sample is based on a custom google search including in total 81 positive and negative events. In addition, we create a subsample which is specific to the incidences of forks and imply that a fork can be categorized as a positive event. The estimation window is set from –180 to –21 days ahead of the actual publication date to estimate valid and robust model parameters. The main event window is set as –20 days before and +20 days after the actual event date (day 0). Thus, the main event window [–20; +20] includes 41 trading days in total. To determine if a certain event, in this case the announcement of a new event, has a significant impact on the asset price, calculate the constant mean return:[17]

$$R_{i,r} = \mu_i + \epsilon_{i,r} \tag{4}$$

[15] Fama (1970) and Andres et al. (2014).

[16] For detailed information please refer to https://eventstudymetrics.com.

[17] Andres et al. (2014).

with

$$E\left[\epsilon_{i,r}\right] = 0 \tag{5}$$

and

$$VAR\left[\epsilon_{i,r}\right] = \sigma_{\epsilon i}^2 \tag{6}$$

μ is calculated by the arithmetic mean of estimation-window returns.

where

$$\hat{\mu}_i = \frac{1}{M_i} \sum_{i=T_0+1}^{T_1} R_{i,r} \tag{7}$$

M_i = number of non-missing returns (estimation window).

The abnormal return is the difference between the excepted returns and the realized returns.

$$AR_{i,r} = R_{i,r} - E[R_{i,r} | \Omega_{i,r}] \tag{8}$$

3.1 Media Coverage

In accordance to a study by SEMrush,[18] the bitcoin price movement exhibits a 91% correlation with Google search trends, which confirms that media coverage and public interest for specific crypto assets have a substantial impact on crypto asset pricing.

We assume that positive and negative news act as crucial value drivers for crypto assets to varying degrees. As some of the observed events occur abruptly and unexpected, we run the event study with both the actual occurrence date of the event and the official publication date, primarily focus-ing on the latter for our event study. In addition, we calculate the cumulative average abnormal returns (CAAR) using the following formula:

$$CAAR_T = \sum_{i=0}^{N} AAR_t \tag{9}$$

with

$$AAR_t = \frac{1}{N} \sum_{i=1}^{N} AR_{i,r} \tag{10}$$

[18] Garanko and Fedorov (2017).

3.2 Event study on positive news events

Table 2 summarizes the results of the event study for the sample of positive events with varying event windows around the event date. As presented in Table 2, positive events pertaining to positive news regarding crypto assets have a substantial economic effect on the price of bitcoin. The event window [–20; +20] exhibits a CAAR of +23.00%. The reported significance tests concerning the t-statistic, the Boehmer and Sign test are significant at the 1% level.[19] The bulk of the CAAR is accumulated prior to the event. The event window [–20; -1] exhibits a CAAR of +16.29% which is significantly different than zero at the 1% level across all reported significance tests.

Table 2: Average cumulative abnormal returns based on the constant mean return model using daily Bitcoin data for positive events (n = 35).

Event Window	Constant Mean Return CAAR	Pos:Neg	Time-Series T-Test	Boehmer	Sign Test
[–20; +20]	+0.2300	25:10	+3.1640***	+3.2444***	+2.7163***
[–20; –1]	+0.1629	23:12	+3.2081***	+2.7743***	+2.0399**
[–10; –1]	+0.1157	24:11	+3.2215***	+3.4063***	+2.3781**
[–3; –1]	+0.0498	22:13	+2.5329**	+3.1246***	+1.7017*
[–1; +1]	+0.0504	26:09	+2.5641**	+2.9823***	+3.0545***
[0; 0]	+0.0309	23:12	+2.7182***	+2.5324**	+2.0399**
[0; +10]	+0.0761	19:16	+2.0216*	+1.9553*	+0.6870
[0; +20]	+0.0671	22:13	+1.2902	+1.5580	+1.7017*

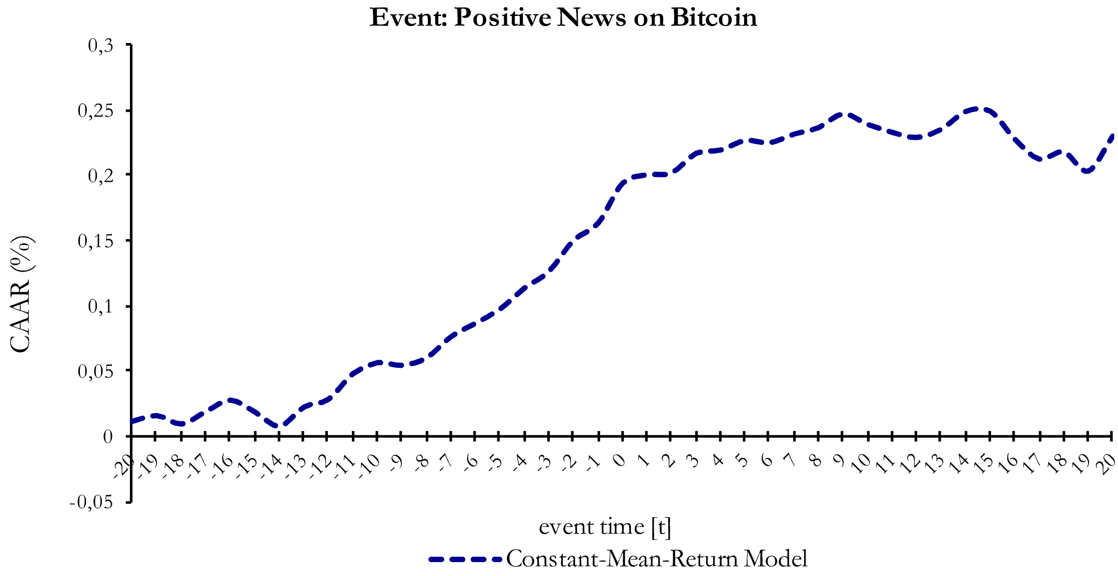
'***' sign. on the 1% level '**' sign. on the 5% level '*' sign. on the 10% level

Even on the actual event date [0; 0], we still calculate a CAAR of +3.09% which is significant at the 1% level based on the t-statistic. The alternative significance tests report a statistical significance at the 5% level. The CAAR on the event date suggests that even without holding material inside information, a crypto investor can get hold of some of the excess returns by trading on the positive event directly after the information becomes public. The economic effect remains positive after the event day. As such the event window [0; +20] exhibits a CAAR of +6.71%, which is statistically significant at the 10% level for the sign test. The alternative test statistics are not significant. The strong magnitude of the positive CAARs prior to the event date implies that there is evidence for significant insider

[19] Please refer to Andres at al. (2014) for a detailed explanation for the event study methodology.

trading in anticipation of a positive event. Figure 3 underlines this hypothesis and shows that the first surge of the CAARs takes place around 14 days prior to the event date. Thereafter the CAARs tend to drift sideways with marginal economic and statistical impact.[20]

Figure 3: Average cumulative abnormal returns based on the constant mean return model using daily Bitcoin data for positive events (n = 35).



3.3 Event study on negative news events

Table 3 summarizes the results of the event study for the sample of negative events. We report an economically and statistically significant effect on bitcoin returns. The event window [–20; +20] exhibits a CAAR of –24.13%. In general, events seem to have an equal price impact regardless of the sign and direction. The t-tests reports a statistical significance at the 1% level. The sign test only indicates a statistical significance at the 10% level. In contrast to the positive events sample, the negative events do not show a statistical significance prior to the actual event date. All event windows prior to the event [–20; –1], [–10; –1] and [–3; –1] remain statistically largely insignificant.

The actual event date [0; 0] exhibits a CAAR of -6.54% which is economically and statistically significant at the 1% level across all significance tests. All event windows after the event date remain statistically significant [0; +10] and [0; +20]. As such the event window [0; +20] exhibits a CAAR of – 6.24%, which is statistically significant at the 1% level for the t-test. The alternative statistics are statistically significant at the 5% level. Surprisingly, the downward trend starts ap-proximately 12 days prior to the event date. The observed graph in Figure 4 gives rise to the presumption that inside

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[20] Please refer to Andres at al. (2014) for a detailed explanation for the event study methodology.

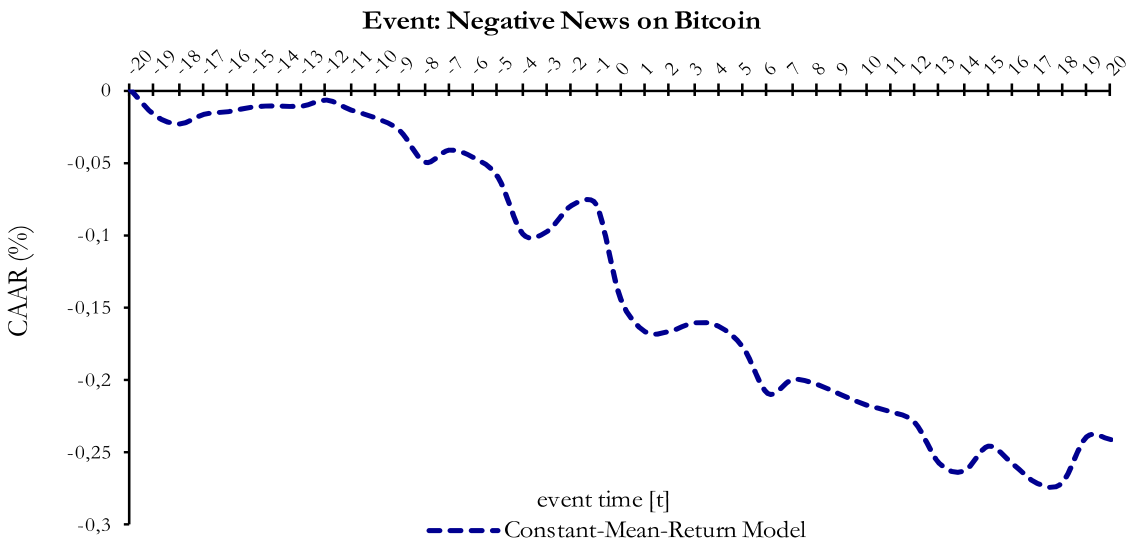
Table 3: Average cumulative abnormal returns based on the constant mean return model using daily Bitcoin data for negative events (n = 40).

Event Window	Constant Mean Return CAAR	Pos:Neg	Time-Series T-Test	Boehmer	Sign Test
[−20; +20]	−0.2413	14:26	−3.1619***	−2.1196**	−1.7418*
[−20; −1]	−0.0789	18:22	−1.4802	−0.4000	−0.4765
[−10; −1]	−0.0653	16:24	−1.7323*	−0.5963	−1.1091
[−3; −1]	+0.0202	17:23	+0.9795	+0.7365	−0.7928
[−1; +1]	−0.0874	12:28	−4.2349***	−2.9806***	−2.3744**
[0; 0]	−0.0654	13:27	−5.4877***	−3.3595***	−2.0581**
[0; +10]	−0.1384	13:27	−3.5013***	−2.7203***	−2.0581**
[0; +20]	−0.1624	12:28	−2.9735***	−2.298**	−2.3744**

'***' sign. on the 1% level '**' sign. on the 5% level '*' sign. on the 10% level

information on negative events is hard to come by and negative events occur on average abruptly and unpredictably.

Figure 4: Average cumulative abnormal returns based on the constant mean return model using daily Bitcoin data for negative events (n = 40).



After the event day, the bitcoin price continues to trend downwards with the CAAR reaching its trough with a negative value of –27.16% on day +17. The largest drop occurs between the event window [0; +13]. Thereafter, the CAARs seemingly move in a sideways drift.[21]

3.4 Event study on fork events

A fork describes a process where a blockchain is split into two similar chains, with the old chain following the initial rules, while the forked chain implements a new set of rules to resolve a certain problem. When the fork is carried out, every token holder within the community will get a token on the newly the forked blockchain. Because these tokens are theoretically exchanged for free to the token holder, we expect positive abnormal returns prior to the event date and negative ab-normal returns on the actual event date, comparable to the stock price dropping by the amount of the dividend on the ex-date. Additionally, the fork event could attract new investors who are initially not invested in crypto assets prior to the announcement of the fork.

The subsequent section examines the magnitude of such price effects and broaches the issue whether it pays off for the investor to hold or overweight an investment position with tokens which are expected to fork in the future. To gain a deeper insight into the dynamics concerning crypto assets, it is essential to evaluate the pricing effect before, during and after a fork event has taken place and test whether there are any significant differences to trading days without the appearance of a fork. In doing so, we analyze following three bitcoin hard forks using the event study methodology explained in the previous section.

The first fork incidence can be traced back for the crypto asset "Bitcoin Cash" occurring on Au-gust 1st, 2017 on block 478558.[22] The second fork incidence is associated with crypto asset "Bitcoin Gold" and occurred on October 24th, 2017 on block 491407.[23] The most current fork incidence can be determined for the crypto asset "Bitcoin Private" occurring on February 28th, 2018 on block 511346.[24] In all three incidences the holder of one bitcoin received one additional unit (token) of the forked crypto asset.

Table 4 illustrates our results for the restricted sample comprising of all bitcoin forks. The sample size is too small to draw any meaningful statistical inferences. Nevertheless, the economic magnitude of the CAARs seems to support our initial hypothesis. As expected, we find a distinct price increase prior the event date with a CAAR of +18.15% in the event window [–20; –1]. On the event date, the price decreases with a CAAR of –5.25%. Future research with a potentially larger sample of forks will need to confirm our initial hypothesis regarding the price effect of fork events.

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21 Please refer to Andres at al. (2014) for a detailed explanation for the event study methodology.

22 https://blockchair.com/bitcoin/block/478559.

23 https://blockchair.com/bitcoin/block/491407.

24 https://blockchair.com/bitcoin/block/511346.

Table 4: Average cumulative abnormal returns based on the constant mean return model using daily Bitcoin data for fork events (n = 3).

Event Window	Constant Mean Return CAAR	Pos:Neg	Time-Series T-Test	Boehmer	Sign Test
[–20; +20]	+0.1557	03:00	+0.8172	+1.5316	+1.6544*
[–20; –1]	+0.1815	03:00	+1.3641	+7.6850***	+1.6544*
[–10; –1]	–0.0281	01:02	–0.2983	–0.7892	–0.6574
[–3; –1]	+0.0173	02:01	+0.3352	+0.45980	+0.4985
[–1; +1]	–0.0167	01:02	–0.3246	–0.7453	–0.6574
[0; 0]	–0.0525	00:03	–1.7663*	–3.2945***	–1.8133*
[0; +10]	+0.0227	02:01	+0.2300	+0.4675	+0.4985
[0; +20]	–0.0258	01:02	–0.1894	+0.0998	–0.6574

'***' sign. on the 1% level '**' sign. on the 5% level '*' sign. on the 10% level

As shown in Table 5, the substantial negative CAAR on the event date seems to be dependent on the magnitude of the price increase prior to the fork event as occurring in the event window [–20; –1].

Table 5: Separate average cumulative abnormal returns based on the constant mean return model using daily Bitcoin data for 3 fork events.

Event Window	Fork 02/28/2018	Fork 10/24/2017	Fork 08/01/2017
[–20; +20]	+0.04019	+0.10331	+0.32349
[–20; –1]	+0.27414	+0.16242	+0.10787
[–10; –1]	–0.07585	–0.02945	–0.02112
[–3; –1]	+0.07879	–0.03773	+0.01705
[–1; +1]	+0.04789	–0.06517	–0.32899
[0; 0]	–0.27829	–0.07600	–0.05380
[0; +10]	–0.21838	+0.10867	+0.17779
[0; +20]	–0.23395	–0.05911	+0.01075

Figure 5 underlines the strong increase in the CAAR prior to the event date and the subsequent drop in prices at the actual event date. After the event, the price tends to move in a sideways drift.[25]

Table 5: Separate average cumulative abnormal returns based on the constant mean return model using daily Bitcoin data for 3 fork events.

Event Window	Fork 02/28/2018	Fork 10/24/2017	Fork 08/01/2017
[–20; +20]	+0.04019	+0.10331	+0.32349
[–20; –1]	+0.27414	+0.16242	+0.10787
[–10; –1]	–0.07585	–0.02945	–0.02112
[–3; –1]	+0.07879	–0.03773	+0.01705
[–1; +1]	+0.04789	–0.06517	–0.32899
[0; 0]	–0.27829	–0.07600	–0.05380
[0; +10]	–0.21838	+0.10867	+0.17779
[0; +20]	–0.23395	–0.05911	+0.01075

4 Efficiency and Arbitrage Options

The following section aims to investigate whether there are any inefficiencies in bitcoin pricing on different crypto asset exchange platforms and whether market efficiencies vary over time. Arbitrage is defined as the existence of a risk-free option to make a profit without a net investment of capital.[26] This option exists when identical assets or similar financial instruments trade on competing markets at different prices. Hence, arbitrage trading allows the exploitation of the existing price inefficiency by simultaneously purchasing and selling an identical asset or similar financial instruments on different exchange platforms. In case a market operates completely efficient, prices of an identical asset or similar financial instruments would anticipate information on all existing trading platforms concurrently. Thus, in the case that the bitcoin market is efficient, we would expect that prices react to new information identically with no price deviations across all trading platforms.

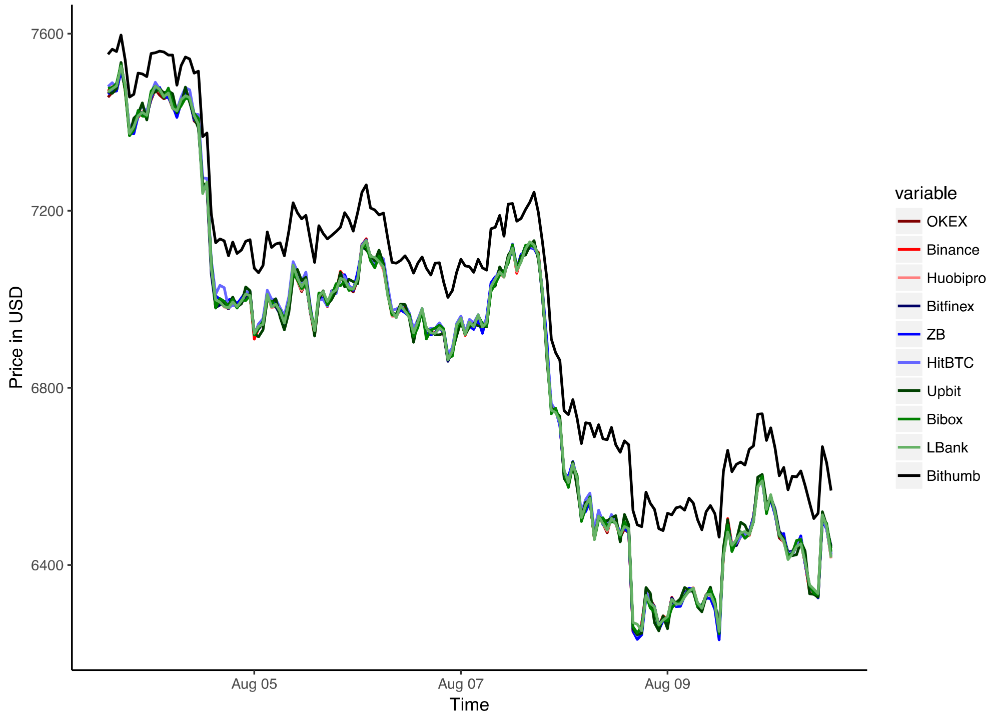
[25] Please refer to Andres at al. (2014) for a detailed explanation for the event study methodology.

[26] Delbaen and Schachermayer (2006).

Figure 6 shows the bitcoin intraday price movement of the ten largest crypto asset exchanges for an estimation window of 80 hours by trading volume. Because Bithumb only trades in South Korean Won, we manually converted the bitcoin price to USD.[27]

Following, crypto asset exchanges OKEX, Binance, Huobipro, Bitfinex, ZB, Upbit, Bibox and LBank exhibit nearly identical pricing for the chosen time frame.

Figure 6: Bitcoin price movement on the 10 largest crypto asset exchanges.



To meet the purpose of this study, we investigate the price differences on the crypto asset ex-changes "Bitfinex" and "Coinbase", two major exchange platforms during the sample period. The bitcoin price differential between the two platforms is calculated as follows:[28]

$$X_t = \left| \frac{P_{bf,t} - P_{cb,t}}{P_{bf,t}} \right| \qquad (11)$$

where X_t is the change in period t in percent. $P_{bf,t}$ is the bitcoin price on Bitfinex, and $P_{cb;t}$ is the bitcoin price on Coinbase, both for period t.

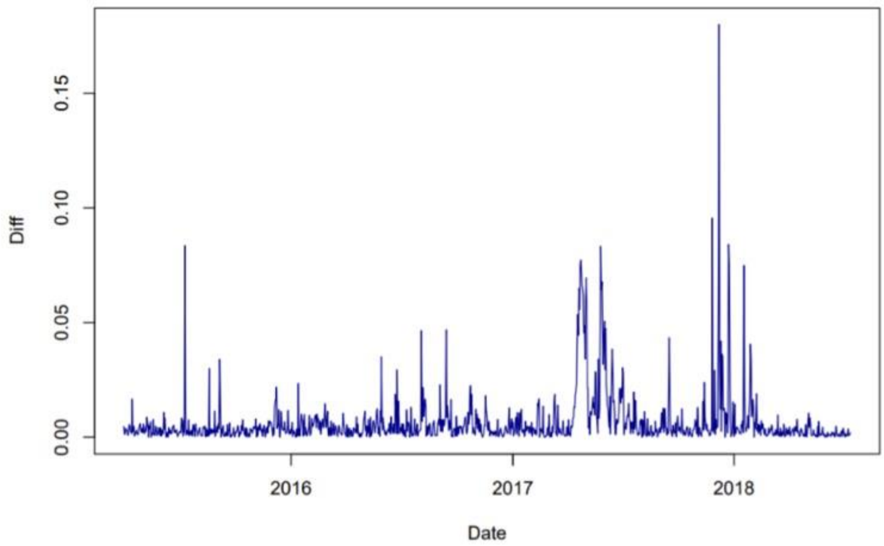
Figure 7 plots the price inefficiency of bitcoin between the two asset exchanges over 1,200 trading days. The plot clearly indicates that there are significant price deviations present for bitcoin on the

[27] Volume data retrieved from https://coinmarketcap.com.

[28] Delbaen and Schachermayer (2006).

two crypto asset exchange platforms, especially in times of high volatility and large price fluctuations. Surprisingly, Figure 7 implies that price indifferences have not noticeably decreased over time yet. The lack of increasing market efficiency may be explained by the fact that the bitcoin market remains illiquid and appears to be in its early stages with rigorous regulations being amiss. However, it should be highlighted that the reported results do not allow firm conclusions to be drawn and rather provides an indication. A more detailed investigation on the depth and breadth of crypto markets may shed light on this matter; especially with the consideration of tick pricing data on bitcoin and other crypto assets. Future research should investigate to what extend crypto assets can evolve to a more mature and efficient market.

Figure 7: Plot of Bitcoin price differential based on two crypto asset exchanges.



The bulk of crypto arbitrage opportunities are driven by differences in trading volumes across separate crypto markets, especially in times of fast moving and volatile crypto markets. Larger crypto asset exchange platforms with higher liquidity exhibit higher trading volume and hence dictate the price movement of crypto assets with smaller crypto exchange platforms often lagging significantly. This is because smaller crypto asset exchanges usually face limited supply and de-mand, leading to lower trading volumes and lower market liquidity. Since crypto exchanges are not linked to one another, smaller crypto exchange platforms cannot adjust the price to exchange average price immediately. As a result, this price differential could potentially be exploited by arbitrageurs and implement trading strategies which would effectively eliminate the presence of price differentials, that is arbitrage strategies are profitable until prices assimilate to the average price across all exchange platforms. Hence, the presence of arbitrageurs has a positive effect on market efficiency.

Yet, there are market anomalies which cannot be exploited by market participants. The most popular case is the so-called "kimchi premium" referring to the price premium on bitcoin on the South Korean crypto currency exchange.[29] Due to stiff regulations in South Korea regarding crypto assets with tight capital controls across the boarder there is a significant price differential which cannot be traded away by exploiting arbitrage opportunities.

In theory, arbitrage strategies can potentially work both ways and arbitrage opportunities can be exploited on both the long- and short-sides of the market based on mispricing of crypto assets on spot and futures market. In case an investor detects an overvalued cash-based or synthetic asset and has a negative outlook, she could express her negative view by engaging in a short position and sell or even short-sell the asset.[30] In case an investor detects an undervalued cash-based or synthetic asset and has a positive outlook, she could take a long position and buy the asset. How-ever, on the spot market crypto arbitrage effectively focuses on (and are restricted to) the long-side of the market engaging in arbitrage strategies. There are only a few selected vendors offering the possibility of short-selling crypto assets on the spot market which comes with a hefty premium. In case an average crypto investor has a negative outlook on bitcoin she is only limited to selling her crypto assets on the spot market to express her negative expectations. An alternative and mores sophisticated way is to take a short position on the futures market or execute strategies based on derivatives.

Three common arbitrage strategies based on crypto assets are reviewed and discussed on theoretical grounds in this chapter: 1) simple arbitrage strategy on crypto spot markets, 2) cash and carry arbitrage with bitcoin futures and 3) crypto triangular arbitrage.

4.1 Simple arbitrage strategy on crypto spot markets

In theory, the simple arbitrage strategy involves the simultaneous sale and purchase of bitcoin (BTC) on separate crypto exchange platforms with diverging spot prices. Given the one-sided crypto arbitrage opportunities on spot markets an investor can purchase a long position in bitcoin on the exchange platform where the BTC price is low and sell bitcoin on the exchange where the BTC price is high. Following hypothetical case shall illustrate how the simple crypto arbitrage works:

Assume, that new (positive) information related to crypto assets becomes public which leads to an instantaneous price surge on crypto markets and prompting high demand for BTC.[31]

Before positive news is released:

On crypto exchange "small coin": Low trading volume with less liquidity. BTC price trades at 5,998 EUR.

[29] Falk (2018).

[30] Short-selling is the process of borrowing an asset and selling it on the spot market. Later, the investor re-purchases the asset and returns the asset to the agency the investor borrowed from with a small fee.

[31] The arbitrage strategy is not restricted to positive events and can also be performed with negative events.

On crypto exchange "big coin": High trading volume with more liquidity. BTC price trades at 6,000 EUR.

After news is released:

On crypto exchange "small coin": Due to low trading volume the BTC price cannot adjust to the new information quickly enough. The BTC price rallies up by roughly 15% and bitcoin trades at 6,898 EUR shortly after the news is released.

On crypto exchange "big coin": Due to high trading volume the BTC price adjusts instantly to the new information and the larger exchange effectively dictates the new price. Accordingly, the BTC price surges up by 20% and trades at 7,200 EUR shortly after the news is released.

Since "small coin" exhibits low trading volume the BTC price cannot adjust to the new information as quickly as on the larger exchange "big coin". Arbitrage investors can trade on this mis-pricing before the price differential is assimilated completely by taking following steps:[32]

- Step 1: Change fiat money to BTC if necessary. This step should be done prior to engaging in a crypto arbitrage strategy.
- Step 2: Buy BTC on crypto exchange "small coin" at 6,898 EUR.
- Step 3: Transfer BTC to crypto exchange "large coin".
- Step 4: Sell BTC on crypto exchange "large coin" at 7,200 EUR and cash in a profit of 302 EUR per BTC.

There are several shortcomings concerning crypto arbitrage which need to be accounted for when implementing arbitrage strategies:[33]

- This strategy requires the hassle of setting up several trading accounts and creating crypto wallets on several (unregulated) exchange platforms under scrutiny. Know your customer (KYC) requirements often place barriers to entry and execute trades on crypto as-sets. Higher requirements need to be met and more information need to be placed with the exchange to trade on higher limits. Also, regulatory requirements may impose a barrier to set up a trading account on a crypto exchange when the bank account is not registered in the country where the crypto exchange reside
- Arbitrage strategy works best when executed instantly once the mispricing is detected. Hence, "coin reserves" should be stored on several crypto exchange platforms which can be costly and increase cyber security risks significantly.

[32] This simplistic example ignores any fees due and trading expenses.

[33] Falk (2018).

- Crypto exchange platforms usually charge fees for trading, depositing, withdrawing and transferring coins. Usually crypto exchange place limits on the amount of BTC that can be transferred or withdrawn from the wallet per day.
- Processing delays and slow transferal times may be a hindrance in executing trades in time, especially in times of high volatility. Arbitrage investors need to account for the processing times of different crypto assets. For instance, Ether transactions are usually much faster processed than bitcoin transactions.
- With the increasing popularity of crypto assets and the potential entrance of institutional investors into crypto markets competition will likely increase in scalping arbitrage profits and making it more difficult for retail investors to execute arbitrage trades.

At the time of writing, CoinMarketCap lists more than 215 distinctive crypto exchange platforms around the world which are largely unregulated and operate disjointedly from one another with crypto transferal being rather slow.[34] The risk arising from the exchange being hacked is imminent and very costly. Hence, investors of crypto investors need to bear higher costs for cyber security compared to other asset classes. Considering trading expenses and transfer fees as well as processing delays, it may be necessary to trade in high volumes to make significant profits from crypto arbitrage. However, trading volumes are usually limited on crypto exchanges, leaving retail investors with clear but not exorbitant arbitrage gains.

However, even if spot market arbitrage seems to be limited by many external constraints, in case an investor has the arbitrage currency and liquidity on different crypto exchanges, spot market arbitrage is an easy to implement side-strategy to achieve additional profits. Since the investor can account for order book depth, he can obtain risk-free profits by simultaneously selling the arbitrage currency on exchange A and buy the same amount of the exchange currency on exchange B, provided that the investor does not have to shift the arbitrage currency or liquidity between the exchanges. All investors which are holding the same currencies on different exchanges should implement a certain price tracking system (such as a bot) to account for possible arbitrage options.

4.2 Cash and carry arbitrage with bitcoin futures

With the launch of crypto futures and other derivatives such as crypto options and forwards, crypto investors can actively take a short position when expecting adverse market movements. Futures contracts are primarily used to hedge or speculate on the underlying asset.

Cash and carry arbitrage consist of a market neutral strategy where an investor purchases a long position in the crypto asset (bitcoin) in the cash (spot) market and simultaneously sells a short position in the bitcoin futures contract with a set expiration date and price in the futures market, or vice versa.

[34] https://coinmarketcap.com/.

This arbitrage strategy seeks to exploit the mispricing of crypto assets between cash and futures markets based on the no-arbitrage price which is set at initiation of the futures con-tract.

The no-arbitrage price is the contractually agreed price at the initiation of the futures contract which does not permit any arbitrage profit at contract expiration. The no-arbitrage concept assumes that there a no transaction costs, there are no restrictions to short selling and borrowing and lending capacities of the investor are unlimited at the risk-free rate.

The no-arbitrage price is defined as:[35]

$$FP \ = Spot\ price\ (S_0)\ +\ Cost\ of\ Carry\ (CT) = S\ x\ (1 + CT) \tag{12}$$

Where: FP = futures price, S_0 = spot price at inception of the contract, C = cost of holding the underlying asset, R_f = annual risk-free rate and T = futures contract term in years

The model implies that the price on the futures contract must equal the spot price at the expiration date of the underlying asset. In case market mechanisms work correctly the cash and carry arbitrage would allow to align prices on futures and spot markets.

Arbitrage investors can trade on potential mispricing by taking following steps:

At the initiation of the contract:

- Step1: Borrow money for the term of the contract at market interest rates.
- Step2: Buy the underlying crypto asset at the spot price.
- Step3: Sell a crypto futures contract at the current futures price.

At contract expiration:

- Step 5: Settle the contract by delivery of the asset or by cash and receive the futures contract price.
- Step 6: Repay the loan and interest.

The arbitrage investor "carries" the asset until the expiration date of the futures contract, at which point the futures contract is cash-settled and the investor makes a riskless profit when the futures contract is more expensive than the actual asset and the profits exceed trading fees and carrying costs on the long position. This is the case when the market price of the futures contract exceeds the no-arbitrage price at contract initiation.

[35] Yeh (2018).

Following simplistic case shall illustrate how the cash and carry arbitrage with bitcoin futures works: Assume, that bitcoin (BTC) trades at 100 EUR in the spot market, whilst the one-month futures contract is currently priced at 107 EUR. Further, assume that carrying costs amount to €5 in total. The cost of carry can be further split into storage, cyber security, insurance and financing costs. Given the fact that the futures contract trades at a premium, the arbitrage investor would take a long position in the spot market and buy the asset at 100 EUR and simultaneously take a short position and sell the one-month futures contract at 107 EUR. The investor "carries" the bitcoin asset until expiration of the bitcoin futures contract. At expiration the futures contract is cash-settled (as opposed to actual delivery) and the arbitrage investor receives a riskless profit of 2 EUR.

Efficient market mechanisms must allow for arbitrage to run in both ways which is partly difficult considering the specific market set up of crypto assets. When crypto futures trade at a premium, investors need to short the futures contract and buy a long position in the bitcoin spot market. This cash-and-carry arbitrage strategy is easily implementable in a real market environment if enough liquidity is given to execute the trades and the cost of carry (such as borrowing costs, storing costs, fees) is manageable. When crypto futures trade at a discount to the spot market, investors can engage in a reversed cash-and-carry strategy by purchasing a long position in a futures contract and short-selling the underlying asset in the sport market. This is where the issue begins with exploiting arbitrage options. Whilst it is straightforward to engage in a long futures position, it hardly possible to short sell the underlying bitcoin asset in the spot market for reason-able costs.

Yeh (2018) shows that crypto arbitrage deviates from the cash-and-carry arbitrage model as de-scribed in textbooks. Further, Yeh (2018) compares the futures price (CBOE bitcoin futures con-tract (XBT Feb18)) against Gemini 4pm bitcoin auction price and shows that there are significant price inefficiencies leading to erratic futures premia which do not gradually diminish over time.[36] Yeh (2018) additionally reports that the cost of carry has been on average around 12% in the first days after the launch of the first bitcoin futures contract. The cost of carry has come down to 5% since its inception in December 2017. However, the limited history of bitcoin futures does not allow to draw any valid conclusion yet.[37] The initiation of crypto futures contracts helps the crypto markets to professionalize, however, it remains challenging to take on a short position in every market situation to execute arbitrage strategies. As discussed above, investors are unable to capture arbitrage profits when futures are too cheap, since there is no easy way to short sell the actual asset in the spot market leading to numerous incidences where the cost of carry was negative.

Whilst institutional investors can assume positive and negative exposure to crypto assets via bitcoin futures they are usually restricted from investing in the actual underlying itself. This is because futures markets are placed on regulated markets.

[36] For further information on the structure of bitcoin futures, refer to the exchanges CME and CBOE.

[37] Yeh (2018).

4.3 Crypto triangular arbitrage with cross-currency rates

A third alternative to engage in crypto arbitrage opportunities involves the trading of three distinctive currency pairs based on cross currency rates. The cross-currency exchange rate is defined as the exchange rate of two currencies implied by the exchange rate of a common a third highly liquid currency such as EUR or USD. Cross rates are needed when there is not enough liquidity in FX market of the desired currency pair. If markets work efficiently then triangular arbitrage should lead to a loss since an investor incurs trading costs when buying and selling currencies within the construction of triangle arbitrage.

An example shall illustrate how triangular arbitrage works with crypto currencies based on bitcoin (BTC), Ethereum (ETH) and Euro (EUR). An investor believes that EUR/ETH is mispriced and assumes an arbitrage opportunity to make a riskless profit using three currency pairs. Assume following foreign exchange rates for the underlying currencies:

ETH:BTC (BTC/ETH) = 0.0760 – 0.07641

ETH:EUR (EUR/ETH) = 443.74 – 444.00

BTC:EUR (EUR/BTC) = 5549.00 – 5549.44

Based on the currency pairs BTC/ETH and EUR/BTC the arbitrage-free cross currency rate for EUR/ETH can be implied as EUR/ETH = 421.72 – 424.03.[38] Following triangular arbitrage strategy would allow to exploit the mispricing of EUR/ETH.

- Step 1: Buy ETH with BTC at the ask price.
- Step 2: Sell ETH for EUR at the bid price.
- Step 3: Buy BTC with EUR at the ask price

Starting with 100 BTC and move clockwise around the triangle executing the arbitrage strategy (BTC to ETH to EUR to BTC) results in 104.6 BTC. The arbitrage gain accumulates in total to 104.6 BTC – 100 BTC = 4.6 BTC. Trading fees, processing delays, volume restrictions and ad-verse market movements are ignored in this simplistic example.[39]

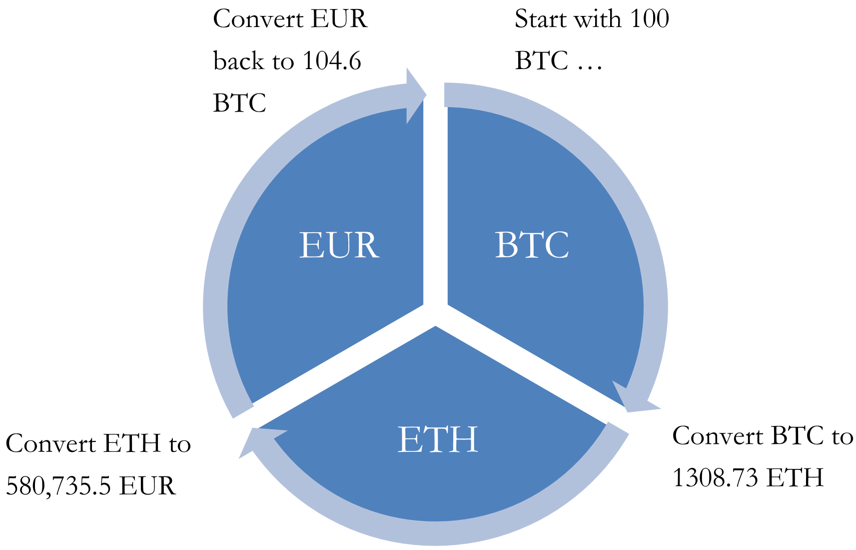
As discussed previously there are an abundance of barriers that make crypto arbitrage strategies rather challenging to implement. This is also the case for implementing a triangle arbitrage strategy. Depositing fiat currency and withdrawing crypto currencies may take some time (taking up to 10 trading days depending on the payment method. In addition, there are might be significant processing delays

[38] Calculating the cross-rate bid: Sell ETH at the bid of 0.0760 (receive BTC) and sell BTC at the bid of 5549 (receive ETH). Resulting bid rate: ETH/EUR = 421.724. Calculating the cross-rate ask: Sell EUR at the ask of 5549,44 (receive BTC) and purchase ETH at the ask of 0.07641. Resulting ask rate: 424.03271.

[39] Roibal (2018).

in verifying trades which could lead to a market situation where prices move against the implemented strategy resulting in unexpected losses.

Figure 8: Triangular arbitrage strategy with BTC, ETH and EUR.



Another future research topic should address the arbitrage opportunities resulting from (1) the trade of bitcoin futures and how crypto asset futures can be integrated into investment strategies, and (2) the trade of currency pairs based on fiat and crypto currencies and how, for instance, triangular arbitrage strategies can be implemented successfully.

5 Practical Implications

Active investors can exploit market inefficiencies by gauging competitive advantages through sensitive information. A well-informed investor should take a long position on crypto assets if the information represents positive news, since the market price will most likely trend upwards. On the other hand, an investor should take a short position on crypto assets when the information entails bad news. Another source of value creation stems from exploiting arbitrage options. The crypto market offers a plenty of opportunities to exploit price inefficiencies, although crypto trading comes along with numerous restrictions. To gauge arbitrage on different crypto exchange platforms requires a registered account on every crypto exchange platform. This can be problematic and time-consuming, since many exchanges have stiff registration procedures for verification purposes. Another issue of processing delays as it needs some time to validate the trades and/or transfer crypto funds from one exchange to the other. With an increasing number of investors seeking an exposure to crypto assets it is getting increasingly difficult to gauge arbitrage options. Retail investors will likely be pushed out of the market to exploit arbitrage options once institutional investors enter the crypto market. Since, December 2017 institutional investors can seek exposure to crypto assets via trading crypto futures contracts. However, the bitcoin futures market is yet too small and illiquid to have a considerable impact on the bitcoin spot market. Announced forks represent an additional source of value creation where a crypto currency is split in two separate digital currencies whilst compensating the token holder of the original token with one additional token the forked blockchain. Betting (speculating) on the occurrence of another fork may suit both an active and passive investment style. Regulators are best advised to push a standard framework and best practices to regulate the crypto market. This would allow institutional investors to jump on the bandwagon.

6 Practical Implications

Undoubtedly, the infant and largely unregulated crypto market may have a tremendous impact on modern portfolio management. Our empirical study infers implications for practitioners and regulators alike. Since its inception, the crypto assets market has been dominated by speculations, manipulative activities and erratic price fluctuations. However, most of these issues can be tackled by rigorous regulations decreasing the entry barrier for institutional investors and increasing market liquidity. The crypto market is still in the early stages and shows signs of severe inefficiencies as documented by the abundance of arbitrage opportunities. Additionally, our event study reveals significant indication for insider trading, especially prior to positive crypto asset related events, which should call on regulators to ensure fair market conditions.

Nevertheless, crypto assets offer a substantial upside potential and diversification benefits due to low correlations with traditional asset classes. However, the shown Spearman and Kendall correlation statistics do not allow a full-blown assessment of the real diversification potential due to the unparalleled high overperformance of bitcoin in the past. To access the real benefit of adding crypto assets to classic investment portfolios, further research regarding tail correlations is necessary. We recommend a left- and right tail risk forecast using auto-regressive methods depending on the degree of randomness embedded in both time series (auto-correlations). Additionally, an event study accounting for crypto price effects based on macro-related events, can further under-line a low and/or insignificant correlation between crypto and traditional asset classes.

By and large, we can illustrate crypto assets as an increasingly viable investment vehicle. Our empirical findings document no evidence for an increase of market efficiency of crypto assets as proxied by bitcoin, leading to the conclusion that crypto markets tend to offer great opportunities to generate excess returns, even in the long run. Since arbitrage and event trading require a fast flow of information and a sophisticated, quantitative and technical trade execution, we can conclude that there are valid arguments for both passive or active investment strategies.

7 Appendix

Event list: positive and negative news on Bitcoin and crypto assets[40][41][42]	Date
01. Nasdaq is open to becoming crypto currency exchange, CEO says	25.04.18
02. The Verge reports the ban of all crypto related ads on Twitter (from 27.3.18)	26.03.18
03. Google announces the ban of all crypto related ads (starting from June)	14.03.18
03. Bitcoin at its lowest value since the November peak (under 6000$)	05.02.18
04. Facebook bans cryptocurrency ads	30.01.18
05. Coincheck (one of Japans biggest cryptocurrency exchanges) was hacked	29.01.18
06. Bitconnect (ponzi scheme) shutting down	16.01.18
07. South Korea threatens to shut down cryptocurrency exchanges	28.12.17
08. Bitcoin price hit all time high just below $20,000	18.12.17
09. CBOE Bitcoin Futures are launched	11.12.17
10. Bitcoin price breaks $10.000 for the first time	28.11.17
11. SegWit2X Cancelled	08.11.17
12. CME announces to launch Bitcoin futures	31.10.17
13. Bitcoin Hard fork: Bitcoin Gold goes live	25.10.17
14. Bitcoin price breaks $5000 for the first time	13.10.17
15. China is shutting down all Bitcoin and cryptocurrency Exchanges	15.09.17
16. Jamie Dimon, head of JP Morgan calls Bitcoin as fraud	12.09.17
17. China bans companies from raising money through ICOs	03.09.17
18. Bitcoin "splits" into Bitcoin and Bitcoin Cash	01.08.17
19. Japan Declares Bitcoin as legal tender	01.04.17
20. SEC denies second Bitcoin ETF application	28.03.17
21. SEC denies Winkelvos ETF	10.03.17
22. Bitcoin price breaks $1000 for the first time in 3 years	03.01.17
23. Donald Trump elected as president, market plummet	09.11.16
24. Bitfinex hacked	02.08.16
25. Second halving day (Block reward decrease)	06.07.16

[40] https://99bitcoins.com/price-chart-history/.

[41] https://www.wikitribune.com/story/2018/01/08/cryptocurrencies/timeline-2018-the-future-of-block-chain-and-cryptocurrencies/33747/.

[42] https://www.cnbc.com/2018/04/25/nasdaq-is-open-to-becoming-cryptocurrency-exchange-ceo-says.html

26. Craig wright claims to be Bitcoin's creator	02.05.16
27. Steam accepts Bitcoin	27.04.16
28. OpenBazaar launched (Bitcoin marketplace)	04.04.16
29. Bitcoin roundtable consensus (scaling etc.)	21.02.16
30. Mike Hearn Quits Bitcoin (development)	14.01.16
31. Gwern and WIRED claim Craig Wright is probably Satoshi Nakamoto	08.12.15
32. Bitcoin sign accepted into Unicode	03.11.15
33. Bitcoin featured on front page of the economist	31.10.15
34. EU declares no VAT (value-added-tax) on Bitcoin trades	22.10.15
35. Gemini exchange launched	08.10.15
36. Bitcoin declared as a commodity by the US regulator	18.09.15
37. Bitcoin XT fork released	15.08.15
38. Mark Karpeles arrested (CEO of Mt.Gox)	01.08.15
39. 2 federal agents plead guilty to silk road theft	01.07.15
40. New York state releases the BitLicense	03.06.15
41. Ross Ulbricht (operator of silk road) sentenced to life in prison	19.05.15
42. Coinbase launches US licensed exchange	26.01.15
43. Bitstamp hacked	04.01.15
44. Charlie Shrem (CEO of exchange BitInstant) sentenced to 2 years in prison	19.12.14
45. Microsoft accepts Bitcoin	11.12.14
46. The slaying of BearWhale (30.000 BTC for 300$ per coin)	06.10.14
47. Paypal subsidiary braintree to accept Bitcoin	08.09.14
48. Dell accepts Bitcoin	18.07.14
49. New York DFS releases proposed "BitLicense" (Bitcoin regulation)	17.07.14
50. US Marshals service auctions 29656 seized Bitcoins	27.06.14
51. Mining Pool Ghash.io reaches 51%	13.06.14
52. Chinese exchanges' bank accounts closed	10.04.14
53. IRS declares Bitcoin to be taxed as property	26.03.14
54. Newsweek claims Dorian Nakamoto is Bitcoin's creator	06.04.14
55. Mt.Gox closes	24.02.14
56. Major exchanges hit with DDOS attacks	07.02.14
57. Chinese Government bans financial institutions from using Bitcoin	05.12.13
58. Exchange rate peaks at 1242$ on Mt.Gox	29.11.13
59. People's bank of china OK's Bitcoin	20.11.13
60. US Senate holds hearing on Bitcoin	18.11.13

61. Dread Pirate Roberts (Silk Road founder) arrested	01.10.13
62. Tradehill (b2b Bitcoin exchange) shuts down (again)	30.08.13
63. DHS seizure warrant against Mt.Gox	14.05.13
64. Increased trading volume breaks Mt. Gox	10.04.13
65. Cyprus Bail-In	25.03.13
66. Bitcoin 0.8 causes brief hard fork	11.03.13
67. Halving day (Block reward decrease)	28.11.12
68. Wordpress accepts Bitcoin	15.11.12
69. Bitcoin Savings & Trust halts payments (ponzi scheme)	17.08.12
70. Linode hacked, over 46000 Bitcoin stolen	01.03.12
71. Paxum and Tradehill drop Bitcoin	11.02.12
72. "The Good Wife" airs "Bitcoin for dummies" TV Episode	19.12.11
73. Mt.Gox hacked	19.06.11
74. Gawker publishes article about the Silk Road	01.06.11
75. Three new exchanges open supporting more fiat currencies	27.03.11
76. Bitcoin price hits 1$	09.02.11
77. Bitcoin protocol bug causes hard fork	15.08.10
78. Mt.Gox opens for business	18.07.10
79. Bitcoin posted on slashdog (popular news and technology website)	11.07.10
80. Two pizzas are first material item purchased using Bitcoin	22.05.10
81. Genesis block established	03.01.09

8 Appendix

Andres, Christian, Betzer, André, Doumet Markus and Limbach, Peter (2014). Event Study. http://eventstudymetrics.com/ (Accessed on 18th June 2018).

Binder, John J. (1998). The Event Study Methodology Since 1969, Review of Quantitative Finance and Accounting, Vol. 11, 111-137.

Box, George E. P., Jenkins, Gwilym M. and Reinsel, Gregory C. (2008). Time series analysis: forecasting and control. In: George E. P. Box; Gwilym M. Jenkins; Gregory C. Reinsel, Pub-lisher Wiley series in probability and statistics.

Chorro, Christophe, Gugan, Dominique and Ielpo, Florian (2015). A Time Series Approach to Option Pricing: Models, Methods and Empirical Performances.

Delbaen, Freddy and Schachermayer, Walter (2006). The Mathematics of Arbitrage, Publisher Springer Finance.

Falk, Tim (2018). The straightforward guide to cryptocurrency arbitrage. https://www.finder.com/in/cryptocurrency-arbitrage (Accessed on 21st August 2018).

Fama, Eugene F. (1970). Efficient Capital Markets: A Review of Theory and Empirical Work, Journal of Finance, Vol. 25, 383-417.

Fama, Eugene F. (1965). The Behavior of Stock-Market Prices, The Journal of Business, Vol. 38, 34-105.

Franke, Juergen, Hafner, Christian M. and Huerdle, Wolfgang (2004). Einfuehrung in die Statis-tik der Finanzmaerkte. In: Statistik und ihre Anwendungen. Vol. 2.

Hileman, Garrick and Rauchs, Michel (2017). Global Crypto Currency Benchmaking Study. Cambridge, Centre for Alternative Finance, University of Cambridge.

Klein, Tony, Hien, Pham Thu and Walther, Thomas (2018). Bitcoin Is Not the New Gold: A Comparison of Volatility, Correlation, and Portfolio Performance, International Review of Financial Analysis, Forthcoming.

Mandelbrot, Benoit (1963). The Variation of Certain Speculative Prices, The Journal of Business, Vol. 36, 394-419.

Mehra, Rajnisch and Prescott, Edward. C. (1985). The Equity Premium: A Puzzle, Journal of Monetary Economics, Vol. 15, 145-161.

Miller, Merton H. and Modigliani, Franco (1961). Dividend Policy, Growth, and the Valuation of Shares, The Journal of Business, Vol. 34, 411-433.

Moreira, Alan and Muir, Tyler (2017). Volatility Managed Portfolios, The Journal of Finance, Vol. 72, 1611-1644.

Garanko, Jana and Fedorov, Konstantin (2017). SEMrush cryptourrencies study: search vol-umes trends. SEMrush. https://d21buns5ku92am.cloudfront.net/46166/documents/34171Cryptocurren-cies%20study%20by%20SEMrush-405170.pdf (Accessed on 1st June 2018).

Roibal, Joaquin (2018). Bitcoin Bot – Triangular Arbitrage Python Binance Crypto Trading Bot. https://medium.com/@BlockchainEng/triangular-arbitrage-with-cryptocurrency-on-binance-ex-change-with-python-videos-and-code-real-bc63d0905d05 (Accessed on 21st August 2018).

Shapiro, Samuel and Wilk, Martin (1965). An analysis of variance test for normality (complete sam-ples), Biometrika, Vol. 52, 591-611.

Tsay, Ruey S. (2005). Analysis of Financial Time Series, Series in Probability and Statistics.

Yeh, Michael (2018). Bitcoin Futures: Promises and Pitfalls. https://medium.com/ironchain-capi-tal/bitcoin-futures-promises-and-pitfalls-a25186534b57 (Accessed on 21st August 2018).