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How Do Large Stakes Influence Bitcoin Performance? Evidence from the Mt.Gox Liquidation Case

by

Thomas Kremser, Sven Radszuwill, André Schweizer, Bernhard Steffek

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WI-998

University of Augsburg, D-86135 Augsburg
Visitors: Universitätsstr. 12, 86159 Augsburg
Phone: +49 821 598-4801 (Fax: -4899)

University of Bayreuth, D-95440 Bayreuth
Visitors: Wittelsbacherring 10, 95444 Bayreuth
Phone: +49 921 55-4710 (Fax: -844710)

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HOW DO LARGE STAKES INFLUENCE BITCOIN PERFORMANCE? EVIDENCE FROM THE MT.GOX LIQUIDATION CASE

Research paper

Kremser, Thomas, FIM Research Center, University of Augsburg, thomas.kremser@student.uni-augsburg.de

Radszuwill, Sven, FIM Research Center, University of Bayreuth, sven.radszuwill@fim-rc.de

Schweizer, André, FIM Research Center, University of Bayreuth, andre.schweizer@fim-rc.de

Steffek, Bernhard, FIM Research Center, University of Augsburg, bernhard.steffek@student.uni-augsburg.de

All authors contributed equally to this manuscript

Abstract

Bitcoin as the first and still most important decentralized cryptocurrency has gained wide popularity due to the steep rise of its price during the second half of 2017. Because of its digital nature, Bitcoin cannot be valuated exclusively with fundamental approaches, which is why factors such as investor sentiment have become a common alternative to capture its performance. In this work, we studied whether and how the sale of Bitcoins from the insolvency assets of Mt.Gox, which represent about 1.1% of the current global total, relates to Bitcoin price movements. We used social media sentiment analysis of Twitter data to examine how investors are influenced in their decision to buy or sell Bitcoin when confronted with the trade actions of Nobuaki Kobayashi, the trustee in charge of the Mt.Gox case. We built a vector error correction model to analyse the long-run relationship between cointegrated variables. Our analysis confirms the positive association of Bitcoin performance with positive Twitter sentiment and tweet volume and the negative association with negative sentiment. We further found empirical evidence that Mt.Gox selloff events have a lasting negative impact on the Bitcoin price and that we can measure this effect by Twitter sentiment and tweet volume.

Keywords: Bitcoin, Sentiment Analysis, Blockchain, Event Study, Mt.Gox.

1 Introduction

The introduction of Bitcoin as the first electronic peer-to-peer payment system represents the first productive use case of blockchain technology (Nakamoto, 2008). Various experts attribute disruptive potential to blockchain as it allows to process (payment) transactions without a centralized payment provider. Bitcoin's value is backed up neither by any commodity (e.g. gold) nor by any legal institution, but instead by the trust in algorithms that guarantee for scarcity and distributed allocation through the internet (Grinberg, 2012). To allow users to exchange Bitcoin for common fiat currencies such as USD or EUR, exchange platforms have emerged. Mt.Gox was the first and, up to its bankruptcy in February 2014, the largest Bitcoin exchange platform that accounted for 70% of all Bitcoins ever traded until then (Vigna, 2014; Ito and Howe, 2016). The bankruptcy of the Tokyo-based exchange was allegedly caused by a cyber-attack during which around 850,000 Bitcoins worth 480 million USD at that point were stolen, which represented about 7% of the global total of Bitcoins (Takemoto and Knight, 2014). Even though Mt.Gox had cited transaction malleability, a particular manifestation of double-spending attacks, as a main reason for the loss, investigations are still ongoing as the trials of the former Mt.Gox CEO, Mark Karpeles, have not led to a final verdict yet (Das, 2017; Berman, 2018). Irrespective of a plausible explanation for the theft itself, during the course of an extensive rescreening of all their wallets in March 2014, Mt.Gox found an old digital wallet used prior to June 2011 with 200,000 Bitcoins (Karpeles, 2014; Knight, 2014). As a result of Mt.Gox's liquidation, the bankruptcy trustee Nobuaki Kobayashi transferred these Bitcoins to so-called "cold wallets" and started to sell them in December 2017 on behalf of former creditors (Kobayashi, 2018). These Mt.Gox selloff events were followed by increasing uncertainty in the crypto market, accompanied by substantial losses of nearly all cryptocurrencies listed on the market throughout the first half of 2018 (Verma, 2018). The concurrence of these above mentioned factors allows us to enter this research environment with the aim to find a relation between these selloff events and Bitcoin performance

Research suggests that soft information like media coverage or media sentiment are among the most dominant factors to value cryptocurrencies and analyse their market performance (Glaser, Haferkorn, Weber and Zimmerman, 2014; Cheah and Fry, 2015). Since social media platforms like Twitter catalyse the distribution of new information within the Bitcoin community, they are utilized by investors to anticipate trading behaviour of large stakeholders (Murphy, 2018). The reactions to these Mt.Gox selloff events represent a good indication of an impact on Bitcoin prices and, once investigated, help to improve the understanding of Bitcoin price dynamics and relevant influence factors. However, so far research lacks behind in utilizing the explanatory power of social media to comprehensively analyse and determine the impact of large-stake investors' sales activities on the Bitcoin price. The case of Mt.Gox serves as a proxy for other major investors, such as Cameron and Tyler Winklevoss, who reportedly still own around 1% of the cryptocurrency's dollar value equivalent (Martin, 2017), or Satoshi Nakamoto, who is widely regarded to own around 6% of all Bitcoins (Lerner, 2013). Therefore, we seek to employ Twitter data as a state-of-the-art approach to gather user-generated content in order to determine the overall opinion of a large number of people (Dickinson and Hu, 2015). In the crypto context, this has been successfully applied before (Garcia, Tessone, Mavrodiev and Perony, 2014; Kim et al., 2016; Stenqvist and Lönnö, 2017) as Twitter provides a suitable environment to capture quick information dissemination and accounts for influencer-follower relationships as well (Mai et al., 2018). We aim to empirically analyse the reactions of the Bitcoin market to Mt.Gox selloff events and derive the following research question:

What effects of Mt.Gox cold wallet trading activities on the Bitcoin price can be analysed and explained through Twitter data?

To answer our research question, we study the Bitcoin sales events of the Mt.Gox case and analyse related 787,308 tweets. In particular, our approach involves the collection of historical Twitter data from January 2016 until April 2018. Further, we conducted sentiment analysis on our tweet collection, aggregated the daily sentiment to a sentiment score and continued with well-established time series analysis measurements. To evaluate our findings we follow Georgoula et al. (2015), who conducted a similar statistical evaluation in the field of Bitcoin.

Our research contributes to the current body of knowledge in the following ways: First, we propose a methodological framework for the utilization of social media data as indicator for future Bitcoin market dynamics. Second, this framework allows derive evidence of how the Mt.Gox selloff events influenced the price of Bitcoin. Third, our work extends current literature on event-study related analysis of Bitcoin price formation. Fourth, to the best of our knowledge, we are the first to examine the impact of a large stakeholder's trading activities on Bitcoin performance. Fifth, we highlight promising avenues for further research in the fields of cryptocurrency market and social media analyses.

The remainder of this paper is organized as follows: Section 2 highlights the technical and economical foundations of cryptocurrencies and Bitcoin in particular. It also contains a brief summary of the results of related studies. Section 3 describes the methodology applied in our study and its practical implementation on our dataset. Section 4 presents our results and their fit to current literature. In Section 5, we discuss our results and state our conclusions as well as recommendations for further research.

2 Theoretical Background and Related Work

2.1 Bitcoin and Cryptocurrencies

Bitcoin is a digital and decentralized currency, not backed by any governmental or other legal entity and not coupled to the value of any commodity (Grinberg, 2012). From a systemic point of view, Bitcoins are an incentive for contributors to provide their resources, which are computing time and electricity, and act as nodes in the decentralized, distributed network accessible through a software program called the Bitcoin client (Nakamoto, 2008). In order to guarantee the scarcity and tradability of Bitcoins, a publicly observable source code, often referred to as protocol, sets out the rules for the system (White, 2014).

The global availability and the employed Proof-of-Work consensus mechanism of Bitcoin lead to a variety of influential factors on its price. Seetharaman et al. (2017) summarized these as regulation, technology, economy and means of payment, with regulation having the most immediate need to be taken into consideration. In this context, Kristoufek (2015) has shown a high correlation between announcements of regulation regarding Bitcoin in China and the Bitcoin price. Griffin & Shams (2018) discovered that the unprecedented hike of the Bitcoin price during the second half of 2017 with a peak around 20,000$ was partially manipulated by the purchase of Bitcoin with Tether on the Bitfinex exchange. Further, certain trading activities such as counterfeiting orders on exchange platforms (spoofing), which are illegal in the regular stock market, go unremedied in most cryptocurrency markets (Madore, 2017). This leads to professional traders deliberately capitalizing on these market flaws as a result of insufficient regulation (Coppola, 2018).

Through projecting such occurrences on the question of cryptocurrency valuation, we have a sound reason to assume that fundamental valuation cannot exhaustively describe Bitcoin performance. In one of the first publications dealing with this phenomenon, Kristoufek (2013) suggests that digital currencies are virtually decoupled from the real economy, which can be concluded by the impossibility to explain Bitcoin price movements with well-established economic and financial theories – e.g. the discounted cash flow model. Among the most dominant factors to value cryptocurrencies, previous research suggests the influence of soft information like media coverage or media sentiment (Glaser et al., 2014; Cheah and Fry, 2015), which might be visible in particular on social media networks such as Twitter or Reddit (Kaminski and Gloor, 2014).

2.2 Twitter Sentiment Analysis

Twitter as a widely used microblogging platform has become increasingly attractive throughout different disciplines as a digital laboratory to study socioeconomic phenomena based on postings (tweets). The wisdom of the crowd concept justifies the approach of reducing noise of individual judgements through aggregation in order to generate a more comprehensive and accurate prediction (Surowiecki, 2004; Chan and Chong, 2017). In that context, Kwak et al. (2010) support the idea of Twitter conforming to an instant news network, as 85% of the topics trending on Twitter refer to events with current news coverage.

Antweiler and Frank (2004) and Das and Chen (2007) have pioneered the forecasting power of data from Internet message boards on stock market development, numerous researchers have drawn on a similar approach. Bollen et al. (2011), for example, show that there is a correlation between tweet mood covering several emotional dimensions and the value of the Dow Jones Industrial Average (DJIA). Zhang et al. (2011) further conclude that social media sentiments qualify as a predictor of financial market movements. These findings are further supported by Sprenger et al. (2014), who conclude that tweet features might be used as valuable proxies for the formation of investors' beliefs and their behaviour on the market. This suggests that the core feature of sentiment analysis is to computationally study peoples' opinions (Liu and Zhang, 2012). Thus, we utilize this feature by analysing topic-related tweets. However, there is no unambiguous prediction period which is most appropriate for the analysis of Twitter sentiment.

Next to sentiment, researchers found evidence that the posting volume of tweets itself already adds a viable source of information with a reasonable forecasting power that could be used to improve existing models (Mao, Wei, Wang and Liu, 2012; Corea, 2016). Zheludev et al. (2014), however, concluded that sentiments based on social media do more often lead financial markets than such based on social media volume, with the latter still demonstrating several statistically-significant results.

2.3 Applications of sentiment analysis in the crypto market

Given these results discovered with stock prices, it is not surprising to observe the application of social media sentiment in the cryptocurrency valuation research domain. Early publications focus on the evaluation of search engine query volumes as a manifestation of public attention (Kristoufek, 2013; Garcia et al., 2014; Matta, Lunesu and Marchesi, 2015; Bleher and Dimpfl, 2018) rather than on the investigation of social media sentiment. One approach that combines the Twitter sentiment, the search engine query volume dimensions with additional economic and technological variables can be found in Georgoula et al. (2015). Their estimation of a vector error correction model (VECM) suggests an impact of the total number of Bitcoins on the market and the S&P 500 index quotation on the underlying long-run relationship. Mai et al. (2015) used a related approach and applied vector autoregression (VAR) for hourly data and a VECM for daily data. They found Bitcoin price to be significantly influenced by Twitter sentiment only for hourly data. Further incorporations of VECM can be found in Zhu et al. (2017), Kavvadias (2017) and Kristoufek (2013).

Few researchers have conducted studies on how specific Bitcoin-related events impact its price. Gulker (2018) provides a mapping of the largest daily price changes with their potential event-based reasons as well as a clustering of news types. Other studies failed to demonstrate significant impacts of events on Bitcoin performance based on Pearson correlation analysis (Pryzmont, 2016) or a cumulative abnormal return method applied on a market model, with the return of the MSCI world index representing the market return (Seys and Decaestecker, 2016). In general, market models are intensively used in Finance, where they are often employed in the event study methodology together with OLS, which is used to estimate results. Even in the stock market, this approach has been described as problematic and inferior to estimators that are robust to outliers and high leverage points (Sorokina, Booth and Thornton, 2013). As Bitcoin prices and returns generally demonstrate a different distribution behaviour compared to stocks or bonds (Chu, Nadarajah and Chan, 2015; Kavvadias, 2017), a statistical VECM for the estimation of the normal returns as shown by Kristoufek (2013) seems more promising.

3 Methodology

3.1 Research Process and Theoretical Model

To answer our research question profoundly, we follow an orchestrated four-phase research process. First, we collect and filter Twitter data related to Bitcoin and Mt.Gox. Second, we apply a sentiment analysis and use SentiStrength to aggregate the Twitter sentiment. Third, we construct a statistical model that explains the general interdependencies between Twitter sentiment, tweet volume and the Bitcoin price. In the fourth phase, we set up an event study to examine the particular effect of Mt.Gox selloff events on the Bitcoin price performance. We found various studies employing parts of our research process distinctly, albeit with mostly different exogenous variables. We did not find a study that combines statistical model and event study within the crypto context yet. Hence, we expand previous work that relies on statistical models by incorporating an event study approach (Venkatesh, Brown and Bala, 2013) We illustrate our research process and the most relevant studies we relied on in Figure 1. The research phases three and four are commonly referred to as econometric analysis and are also reflected in our variable model (Figure 2)

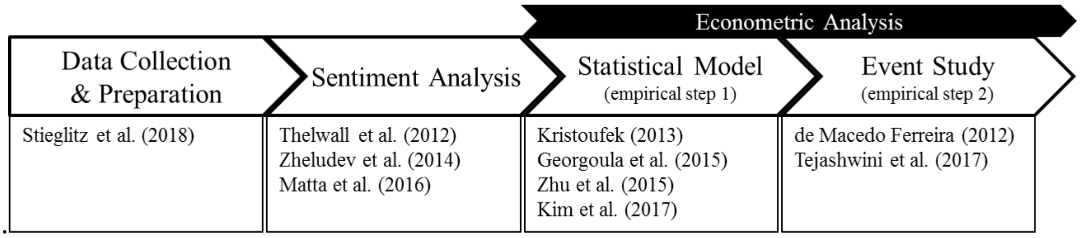

Figure 1. Research process and relevant literature

Numerous researches on Bitcoin valuation operate in an economic environment similar to the capital market, making it inevitable to define the theoretical frame in which we operate throughout this study. This is particularly important as we acknowledge that cryptocurrencies follow economic properties distinct from the ones present in the capital market (Chiu and Koeppl, 2017). Hence, according to Yermack's (2015) and Wu and Pandey's (2014) propositions, we assume that standard supply and demand interactions like the Fisher equation (associated with the quantity theory of money; 1930) do not apply to the crypto environment and that macroeconomic variables of an issuing country or institution do not exist therein. Instead, as proposed in Kristoufek (2013) and Jiang (2013), we link the supply function of the Bitcoin Market to the algorithm developed and published by Satoshi Nakamoto (2008) and the demand function to investors‘ expected future profits. Thus, we consider Bitcoin as an investment asset whose demand is a reflection of speculative behaviour associated with investor expectation about its future price development (Hanley, 2013; Cheah and Fry, 2015). To capture these hopes and feelings, we rely on Twitter data as a proven measure of investors' sentiment in this matter.

In Figure 2 we illustrate the empirical variable model, underlying our econometric analysis. Consistent to our research process, the empirical variable model comprises two components, reflecting research phase three and four. The first component describes the relationship between variations in Twitter activities and the Bitcoin price development. The set of variables influencing daily Bitcoin closing price (*btcprice: daily closing price, quoted in USD*) are: positive Twitter sentiment (*sentpos: sum of daily positive Twitter sentiment*), negative Twitter sentiment (*sentneg: sum of daily negative Twitter sentiment*) and tweet volume (*volume: number of daily tweets on Bitcoin and Mt.Gox*). The second component allows us to inspect how this relationship behaves in the context of Mt.Gox selloff dates, which are dates where the trustee sells a certain amount of Bitcoins (usually multiples of 2,000 BTC) from the Mt.Gox cold wallets under his administration. Since we conduct an event study based on Pynnönen (2005), de Macedo Ferreira (2012) and Tejashwini et al. (2017) our model includes a dummy variable (*mtgoxevents: dummy variable of Mt.Gox event windows*) that indicates which data points from the time series need to be considered for each event window (Fantazzini, Nigmatullin, Sukhanovskaya and Ivliev, 2016). An event window represents the time period around a particular selloff event where the effect of same is examined with respect to the variables in component 1 of our empirical variable model.

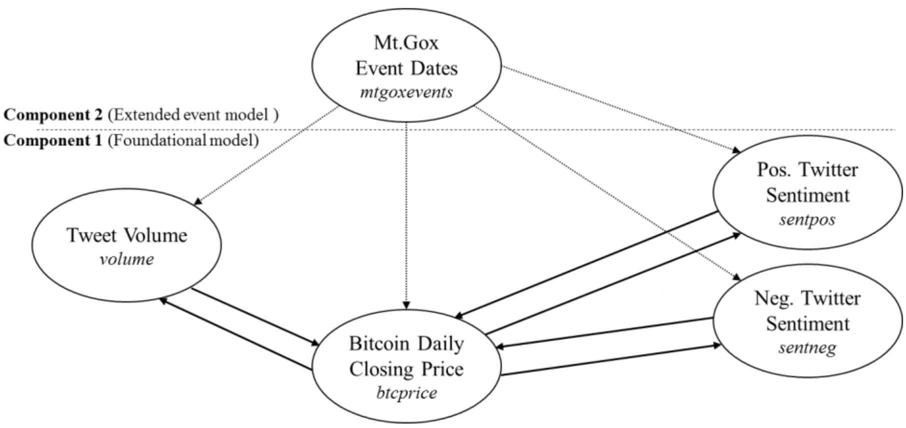

Figure 2. Empirical Variable Model

3.2 Research Phase 1: Data Collection and Preparation

We collect a dataset of daily tweets of the period between January 1, 2016 and April 25, 2018. We use the *Twitterstream* dataset available on archive.org to receive a random sample of 1% of the global tweets. This represents the maximum share of historical tweets one can access free of charge (Kerg, Roedler and Seeber, 2014; Borruto, 2015). Our dataset includes over 3,386,880,000 tweets in a JSON-format from a time period of 821 days. Hence, we are able to analyse a large period that contains, amongst others, the strongly bullish 4th quarter of 2017 as well as the rather bearish 1st quarter of 2018.

To prepare the data we follow the social media analytics process of Stieglitz et al. (2018). The first step involves the removal of all attributes contained in each JSON-format tweet except *Tweet id, Tweet text, Date of creation, User id, User geolocation* and *Tweet language*. We filter the data by using character-based text identification on the text attribute of each tweet. To curtail the whole dataset, we focus on gathering tweets containing the keywords "BTC", "Bitcoin" and "Mt.Gox" as well as their representations in the hashtag attribute "#BTC", "#Bitcoin" and "#Mt.Gox" (including lowercase and alternative spellings). Based on the *Tweet language* attribute (*lang*), we also filter out all non-English tweets as we cannot analyse them in conjunction with a mainly English lexicon. Next, in order to take incorporated sentiment properly into account, we substitute all Unicode characters representing emoticons with their respective adjectives, e.g. the Unicode character for the happy smiling face ☺, U+263A, with the text "happy". We also remove all links from the tweets as they frequently contain random manifestations of above-mentioned keywords, which would dilute our sentiment and volume variables. Upon completion of the filtering process, 787,308 tweets remain in our dataset. We collect Bitcoin prices from coinbase.com, using daily closing values, and take the exhaustive list of Mt.Gox selloff events from the table available on Cryptoground Mt.Gox Cold Wallet Address Monitor (Durden, 2018; Kobayashi, 2018).

3.3 Research Phase 2: Sentiment Analysis

Sentiment analysis of research phase two allows to identify whether the expressed opinion of an author is positive or negative about a particular subject or context. In our work, we conduct the sentiment analysis through the use of SentiStrength, a state-of-the-art lexicon-based classifier that has been applied in related research before (Zheludev et al., 2014; Matta, Lunesu and Marchesi, 2016). The lexicon-based approach is a common method to interpret opinions expressed within a text A lexicon is a collection of features, usually comprised of words and their sentiment classification (Taboada et al., 2011). SentiStrength is particularly suitable for short, informal social web texts such as Twitter and MySpace comments and builds up on its core of 2310 words and word stems taken from the Linguistic Inquiry and Word Count (LIWC) program (Pennebaker, Mehl and Niederhoffer, 2003). It further incorporates a booster word list, a negation word list, a question word list, a slang word list and an idiom list, as well as continuously implemented improvements such as the capability to detect repeated letters within a word for sentiment emphasis (Thelwall, Buckley and Paltoglou, 2012).

Based on a dual 5-point scheme for text classification, each tweet is assigned a positive score from 1 (no positivity) to 5 (very strong positivity) and a negative score from -1 (no negativity) to -5 (very strong negativity). SentiStrength therefore relies on two sentiment scales rather than one, which is methodologically superior as tweets may exhibit positive and negative sentiment towards its readers, and people evidentially are able to experience two oppositely valenced emotions simultaneously (Berrios, Totterdell and Kellett, 2015; Vilares, Thelwall and Alonso, 2015). Siganos et al. (2017) support this finding as they emphasize the concept of divergence of sentiment, which expresses the difference in how investors interpret public information about a stock. Their study reveals that divergence of sentiment is highly related to trading activity and consequently affects stock price volatility. Another important part of sentiment analysis is the handling of bots, which often promote initial coin offerings (ICOs) on Twitter. We do not explicitly filter out bots as researchers found evidence that these also influence non-bot users (Gilani et al., 2017). The same conclusion is valid for the trading dimension, where a recent study reveals that human users exhibit increased trading behaviour when induced by trading bots (Krafft, Della Penna and Pentland, 2018).

3.4 Research Phase 3 and 4: Econometric Analysis

We follow an econometric analysis that has been applied by various researchers when analysing time series data and applying statistical models (Kristoufek, 2013; Mai et al., 2015; Georgoula et al., 2015; Zhu et al., 2017). The activities stationarity testing, cointegration testing and vector error correction model are reflected in our research phase three and the first component of our empirical variable model. The activities event study setup and cumulative average abnormal returns calculation are reflected in our research phase four and the second component of our empirical variable model.

3.4.1 Research Phase 3: Statistical Model

In research phase three we aim to determine whether there is an association between variations in Twitter activities and the Bitcoin price development. To achieve this, we set up a vector error correction model based on stationarity and cointegration testing (Johansen and Juselius, 1990). VECM as a statistical model allows to estimate long-term effects and to analyse the short term error adjustment process within one model comprised of cointegrated variables (Nastansky, Mehnert and Strohe, 2014). We use time series data of three variables that represent influencing factors on the Bitcoin price, framing the period from 1 January 2016 to 25 April 2018 on a daily basis. With the construction of a VECM, we formulate an instrument which helps us to understand long-term interdependencies between these endogenous variables. Consequently, we are able to explain the behaviour of each variable from our set as a result of an exogenous impulse (“shock”) affecting one of them.

Stationarity testing
To identify statistical properties of our time series, we test for stationarity to investigate a potential trending behaviour. In order to apply a VECM, non-stationarity of the non-differentiated time series is required. First, we apply natural logarithmic transformation to all endogenous time series to control the problems of frequent outliers and high skewness, which is often related to financial variables. Next, we check whether the investigated log-variables and their respective first differences are stationary or not by running the augmented Dickey-Fuller (ADF) test, the Phillips-Perron (PP) test and the Kwiatkowski–Phillips–Schmidt–Shin (KPSS) test (Phillips and Perron, 1988; Kwiatkowski, Phillips, Schmidt and Shin, 1992; Elliott, Rothenberg and Stock, 1996). The ADF test has a null hypothesis of a unit root (d = 1) against the alternative of no unit root (d < 1), just as the PP test, which is yet meaningful to conduct also as it is robust to serial correlation by applying heteroscedasticity and autocorrelation-consistent (HAC) standard errors. Together with the KPSS test and its null hypothesis of stationarity (d = 0) against an alternative of a unit root (d = 1), these tests form the ideal trio for stationarity vs. unit-root testing and thereby help us to avoid spurious regression (Wolters and Hassler, 2006).

Cointegration testing
In order to describe interaction and disturbance effects between non-stationary time series, we test for cointegration and, if given, apply the vector error correction model (VECM). The purpose of the cointegration test is to check whether the non-stationary time series exhibit stable linear combinations between them. This means that the series y_t (e.g. *btcprice*) and $x_{1t}, \dots, x_{kt}$ (e.g. *sentpos, sentneg, volume*) are cointegrated of order CI(d,b) if all series are integrated of the same order d and there exists a linear combination of them integrated of order d-b. The standard cointegration is based on a CI(1,1) relationship, which says that the series are all integrated of order one (I(1)) and there exists a linear combination $u_t = y_t - a_0 - a_1 x_{1t} - \dots - a_k x_{kt}$ which is I(0), meaning stationary with short memory. In this case, the long-run relationship between the cointegrated variables is given by:

$$u_t = y_t - a_0 - a_1 x_1 - \dots - a_k x_{kt} + u_t \qquad (1)$$

The vector [1, $-a_0$, $-a_1$, …, $-a_k$] is called the cointegrating vector and does not necessarily have to be unique when dealing with two or more variables. Regarding the indices, k indicates the number of cointegrating vectors, while t indicates the period. The lagged residual series u_{t-1} is called the error correction term, which is interpreted as a deviation from the long-term equilibrium. To test for cointegration between multiple variables, we use the Johansen’s trace test and likelihood test (Johansen, 1988, 1991).

Vector error correction model

As a generalization of vector autoregression, the VECM further incorporates long-term corrections and therefore allows us to study short- and long-term dynamics (Engle and Granger, 1987; Enders, 2014). As for our example case of cointegrated CI(1,1) series, VECM(p) with p lags is written as:

$$\Delta y_t = \gamma_1 + \sum_{i=1}^{p} \delta_{1i} \Delta y_{t-i} + \sum_{i=1}^{p} \theta_{1i} \Delta x_{t-i} + \gamma_1 (y_{t-1} - a_0 - a_1 x_{t-1}) + \varepsilon_{1t} \quad (2)$$

$$\Delta x_t = \gamma_2 + \sum_{i=1}^{p} \delta_{2i} \Delta y_{t-i} + \sum_{i=1}^{p} \theta_{2i} \Delta x_{t-i} + \gamma_2 (y_{t-1} - a_0 - a_1 x_{t-1}) + \varepsilon_{2t} \quad (3)$$

The parameters δ_{ji} and θ_{ji} control for the short-term dynamics whereas a_0 and a_1 describe the long-term relationship between x_t and y_t. The parameters γ_1 and γ_2 contain information on the speed of adjustment to the long-run equilibrium, and ε_{jt} is the i.i.d. error term. We present the results of the VECM outlined in the above methodology visualized as impulse response functions. These allow us to estimate the response of all endogenous variables (i.e. *btcprice*, *sentpos*, *sentneg*, *volume*) in our model to an impulse, such as an exogenous shock, on a single variable.

We rely on the same statistical model as Georgoula et al. (2015), however, there are substantial differences in the choice of variables which arise from a different research focus. While they include multiple economic and technical variables in their model to explain Bitcoin performance in general, we solely focus on Twitter Sentiment and Tweet Volume as to purely analyse the effect of Mt.Gox selloff events on Bitcoin performance. Thus, our VECM constitutes the estimator for the event study that extends the above mentioned framework to suit our research objectives.

3.4.2 Research Phase 4: Event Study

In research phase four our fundamental aim is to identify statistically significant deviations of the Bitcoin time series to what would be considered a normal development. To estimate normal Bitcoin prices, we draw on the VECM built in research phase three. We then compare these estimations to the actual Bitcoin prices to identify abnormal deviations that possibly happened in the context of Mt.Gox selloff events. To achieve this, we use cumulative average abnormal returns method (CAAR), which provides the means of comparison for this setting while suggesting the use of returns instead of prices (Barber and Lyon, 1997). If the difference between estimated normal returns and actual realized returns is statistically significant, we assume that the selloff event had a substantial impact on the Bitcoin price development (MacKinlay, 1997; Pynnönen, 2005). In this context, we note that under conventional capital market conditions, estimating normal returns with market models or the CAPM is a valid approach. Given the restrictions for the crypto market outlined above, we aim for an estimation that requires less restrictions and opt for the VECM (Pacheco, 2010; Yang, Huang and Wang, 2013).

Event Study Setup

We apply the general event study setup from Pynnönen (2005) and follow the three-step process applied in de Macedo Ferreira (2012) and Tejashwini et al. (2017).Thus, we start with the event and respective window identification, followed by the estimation of normal returns and the calculation of abnormal returns.

We identified five Mt.Gox selloff events within the analysed time frame. We then define appropriate event windows, which determine the time frame for the investigation of abnormal returns. According to MacKinlay (1997), it is crucial for correct measurement to have only one event per event window. Krivin et al. (2003) further found out that fixed-length event windows are rather inappropriate for studies that focus on a few or a single security. For this reason, we construct a decision mechanism based on comparing an 18-day and a 2-day moving average (MA) indicator on the Bitcoin price. We opt for this interval combination as it provides adequate delimitations of the event windows in order to adhere to the recommendations mentioned above. That way, we configure each separate event window dynamically to the time points of the preceding and the subsequent intersection of the MA indicators. Hence, each Mt.Gox selloff event window is represented in *mtgoxvariables* as the time frame between these MA intersections. We show both MA indicator in Figure 3 where the smooth green line depicts the 18-day MA that is frequently intersected by its 2-day counterpart in red.

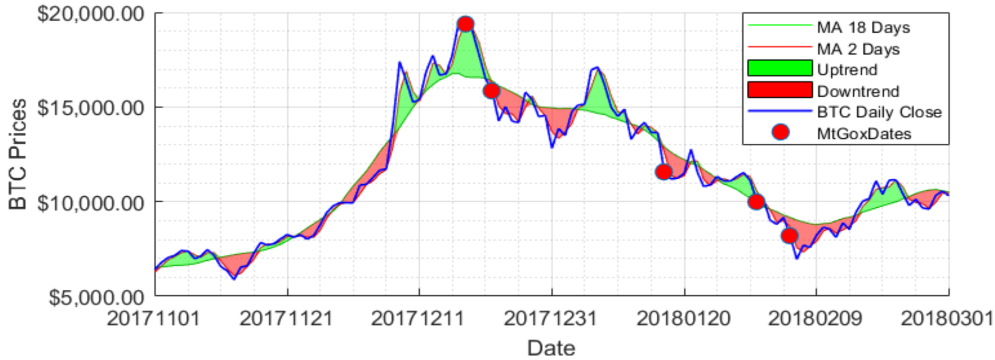

Figure 3. Illustration of Bitcoin price, 18 & 2-day MA indicators and Mt.Gox selloff dates

The determination of the estimation period is usually arbitrary and dependent on many factors such as event frequency and event distribution over the analysed time frame (de Macedo Ferreira, 2012). Hence, we choose to also have dynamically adjusted estimation periods and let each estimation window encompass the time from January 1, 2016 (same for all five events) until the start of the respective event window (different for each event). Furthermore, we assume independence among the Mt.Gox events as these are discrete time points that could not be forecasted based on their previous occurrences. That is why we examine the relation between the endogenous variables and *mtgoxevents* and model latter as an exogenous predictor variable for y_t (e.g. *btcprice*) within the VECM.

Cumulative average abnormal returns

We calculate the normal returns based on our VECM, which serves as our estimator in this context. For our study, we define normal returns as those who occur if there had been no Mt.Gox selloff events lately, disregarding any other events possibly influencing the Bitcoin price. We calculate and analyse the abnormal returns using cumulative abnormal returns (CARs) and cumulative average abnormal returns (CAARs). Abnormal returns can be defined as the difference between the actual return $R_{i,t}$ and the normal return $NR_{i,t}$ on day t of event window i.

$$AR_{i,t} = R_{i,t} - NR_{i,t} \quad (4)$$

Abnormal returns rarely per se useful to determine event effects if used solely, so we need to aggregate the abnormal returns from each event window period [t1, t2] as the cumulative abnormal returns spread (CAR_i) of event window i.

$$CAR_i = \sum_{t=t1}^{t=t2} AR_{it} \quad (5)$$

Then, the cumulative average abnormal returns of each event window periods are calculated as:

$$CAAR_i = \frac{1}{N}\sum_{i=1}^{N} CAR_i \quad (6)$$

Now that we have completed the calculation, we perform a t-test to evaluate if the selloff events significantly influence the Bitcoin price. If its null hypothesis holds, this would not be the case, so the CAAR of a selloff event is zero (H_0: CAAR = 0; H_1: CAAR $\neq$ 0). The standard t-test formula is:

$$t_i = \frac{CAAR}{\sigma_{AR,i}} \quad (7)$$

Regarding the degrees of freedom for the t-test we follow Serra (2002) and use $d = t_1 - t_2 - 2$, which means that we reduce each event window period by 2. The table for the double-sided t-test with $\alpha = 0.05$ gives us the relevant reference value T_i for each selloff event and the null hypothesis is rejected if $|t_i| > T_i$. In such cases, we note that the CAAR are effectively different from zero, which lets us conclude that the selloff event had a significant impact on the Bitcoin price through returns.

4 Results and Interpretation of the Econometric Analysis

4.1 Stationarity & Cointegration Test

We mainly rely on Matlab as computing environment for data preparation, test implementation and plotting. However, we use gretl at some points to plot and verify our empirical results. Initially, we test the stationarity of three transformations of the original series using the ADF, the PP and the KPSS test. The results indicate that *logbtcprice*, *logsentpos*, *logsentneg* and *logvolume* are all non-stationary, but their first differences are stationary, meaning that we can confirm first-order integration (I(1)).

To test for cointegration relationships, we apply the Johansen trace and the Johansen likelihood test and summarize the results in Table 1. Both tests indicate three cointegrating equations at the 0.05 level, which let us draw the conclusion that there exists a long-term dynamic equilibrious relationship between the Bitcoin price and the three variables of our empirical variable model. We model *mtgoxevents* as a dummy variable, thus it is not included in the cointegration test. With *btcprice*, *volume*, *sentpos*, *sentneg*, we continue using logarithmic transformations of the respective time series.

Johansen Cointegration test (ignoring exogenous variables)					
Rank	Eigenvalue	Trace test	p-value	LMax test	p-value
0	0.14180	233.87	0.0000	124.63	0.0000
1	0.071873	109.24	0.0000	60.788	0.0000
2	0.056716	48.456	0.0000	47.586	0.0000
3	0.0010671	0.87015	0.3509	0.87015	0.3509
Corrected for sample size (df = 782)					
Rank	Trace test	p-value	Log-likelihood		9505.39
0	233.87	0.0000	(including constant term)		7192.52
1	109.24	0.0000	**Note: in general, the test statistics above are valid only in the absence of additional regressors*		
2	48.456	0.0000			
3	0.87015	0.3518			

Table 1. Johansen's trace and likelihood tests for cointegration

4.2 Vector error correction model (VECM)

Having discovered the long-term dynamic equilibrious, granger-causal relationship, we are now interested in the dependencies between positive sentiment, negative sentiment, tweet volume and Bitcoin price. We determined the appropriate lag length for our model using the standard test set comprised of Akaike, Hannan-Quinn and Schwarz-Bayesian information criteria (Love and Zicchino, 2006). In case of conflicting indications, we chose the minimizing lag length of the latter (Mai et al., 2015). Based on the information criteria, we use a VECM with six lags (VECM(6)). In Figure 4, we present the impulse response functions for our VECM. The charts show how a variable in our model responds to a shock in the impulse variable. With natural logarithmic transformations, one can interpret the results as percentage changes (Nau, 2014). For better understanding, we display the results as a reaction of Bitcoin price to a 10% shock in the respective variable. However, as VECM results represent permanent shifts in the response variables, we can assume a stabilization of the effect after a longer period.

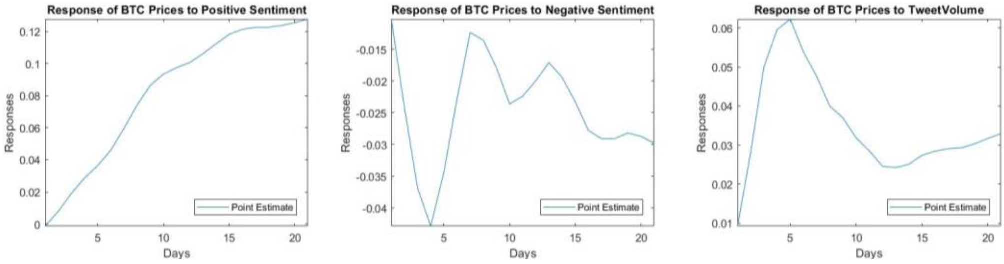

Figure 4. Response dynamics for the foundational model (R^2: 0.565, adj. R^2: 0.548)

Within the first 15 days, positive Twitter sentiment exerts a significant positive influence of about 1.2% on the Bitcoin price before it seems to stabilize its slope on this level. It seems reasonable that a 10% shock in positive Twitter Sentiment is associated with some new market-relevant information that is not yet incorporated in the price, causing it to increase. For negative sentiment, we observe an immediate steep decline of -0.4% shortly after the shock, followed by a similarly steep upwards correction and a consecutive downward movement in a channel pattern resulting in a permanent shift of -0.3%. This is a communication pattern one can often observe on Twitter, expressing an initial negative overreaction that is followed by strong appeasement of crypto fans and bots. The true negative response towards the shock is probably unveiled only in the long run. Our results related to Twitter sentiment are in line with Georgoula et al. (2015), even though we could explain response dynamics in greater detail due to the separation of positive and negative sentiment compared to applying a single sentiment ratio. Regarding tweet volume, we observe that a shock causes a response of 0.6% in the Bitcoin price within the first five days, followed by a decline to the half until the 10th day. In the long run, prices exhibit to increase mildly and converge against a long-term positive shift of 0.4%. This response is related to the one discovered with negative Twitter sentiment. Here, we also observe a strong immediate reaction, followed by a correction and a steady but moderate development in the same direction as the strong initial response. With Tweet Volume, we received different results than Georgoula et al. (2015), who could not find a significant influence on Bitcoin performance. One possible explanation for this could be the extended and more recent timeframe analysed in our study. Therefore, we could interpret from these results that a sudden strong increase in tweets issues more positive than negative tweets and consequently leads to a positive long-term response in the Bitcoin price.

4.3 The Mt.Gox Event Study

First, we determine the event windows and derive respective estimation periods for all Mt.Gox selloff events based on the MA intersections outlined in section 3.4.2. We continue with performing the CAAR method on each event window and find all Mt.Gox selloff event windows to be significant. An overview of our results is provided in Table 2.

Mt.Gox Date	Bitcoins sold	Event Window	Estimation Window	CAAR (in %)
2017/12/18	2,000	2017/12/17 – 2017/12/19	2016/01/01 – 2017/12/17	-0.0500 **
2017/12/22	6,000	2017/12/21 – 2017/12/23	2016/01/01 – 2017/12/21	-0.0563 *
2018/01/17	8,000	2018/01/16 – 2018/01/18	2016/01/01 – 2018/01/16	-0.0669 ***
2018/01/31	6,000	2018/01/30 – 2018/02/01	2016/01/01 – 2018/01/30	-0.0579 **
2018/02/05	18,000	2018/02/04 – 2018/02/06	2016/01/01 – 2018/02/04	-0.0627 ***
***, **, * denote significance at the 0.01, 0.05, and 0.1 levels, respectively.				

Table 2. CAAR results of Mt.Gox selloff events

We continue with presenting a summary of significant variable-lag combinations resulting from the VECM, with *mtgoxevents* having lags up to 6. One can derive from this summary which impact a Mt.Gox event has on each endogenous variable. Further, we explain the lag of the Mt.Gox effect for each variable, indicating the number of days it takes for the effect to manifest after a selloff event (4, for example, represents a lag of 4 days). The results are shown in Table 3.

Mt.Gox effect	Coefficient	Std.Error	t-ratio	p-value
logsentpos				
mtgoxevents_4	0.146470	0.0745427	1.965	0.0498 **
logsentneg				
mtgoxevents	-0.0994333	0.0599217	1.659	0.0974 *
mtgoxevents_4	-0.152399	0.0756441	2.015	0.0443 **
logvolume				
mtgoxevents	0.0982937	0.0592727	1.658	0.0977*
mtgoxevents_4	0.141153	0.0756148	1.886	0.0596*
logbtcprice				
mtgoxevents	-0.0408735	0.00676554	-6.041	2.36e-09 ***
mtgoxevents_1	0.0209314	0.00855440	2.447	0.0146 **
mtgoxevents_3	-0.0237280	0.00792553	-2.994	0.0028 ***
mtgoxevents_4	0.0275419	0.00854070	3.225	0.0013***
mtgoxevents_5	-0.0271497	0.00863087	-3.146	0.0017***
mtgoxevents_6	0.0121125	0.00698316	1.735	0.0832*
****, **, * denote significance at the 0.01, 0.05, and 0.1 levels, respectively.*				

Table 3. VECM results for each significant variable/lag combinations

In Table 3 one can see that both negative Twitter sentiment and tweet volume react significantly to a Mt.Gox selloff event on the day after the event and four days after the event. These results indicate that both variables increase by nearly 10% on the subsequent day, which most likely resembles the quick information dissemination within Twitter outlined before and demonstrates the severe impact of a Mt.Gox selloff event. For the fourth day following the event, we discover even stronger responses of all three explanatory variables, which could be due to lagged responses of the media and/or reflect the simultaneous drawback of negative sentiment described in section 4.2 and the investors' fear of the next selloff-event taking place. We note that, of five selloff events examined, two have been followed by another selloff event within five days or less, therefore adding weight to this potential explanation.

The main result of this event study is provided by the response of prices to a selloff event taking place. The response is characterized by an initial 4% decline in the Bitcoin price on the day after the selloff event, followed by a 2% upwards correction on the subsequent day. We have then left out a non-significant negative continuation of the response on day three, which is proceeded in the again significant -2.4% response on the fourth day. Afterwards, the effect seems to even out as the coefficients continue to have alternating signs on a daily basis. We compare this development to the Bitcoin price response to a shock in negative Twitter sentiment as it exhibits a similar initial decline followed by a considerable correction and a steady negative advancement. Beyond that, we note that the development of the Bitcoin price during the first quarter of 2018 fits well to our results as it entails a steady but rather moderate bearish development with a few saliently strong downside movements.

5 Conclusion

In this paper, we studied the relationship between Twitter data and the Bitcoin price in the context of Mt.Gox selloff events. Our results provide empirical evidence of the impact of Bitcoin/Mt.Gox-related tweets on the Bitcoin price. Our research demonstrates the significant impact of Mt.Gox selloff events on Bitcoin prices and supports the idea of this impact being measureable through sentiment and volume. We spatialize our results discovered throughout both empirical steps in Figure 5. The coefficients between variables of the foundational model represent log-log relations, those between the foundational model variables and *mtgoxevents* show log-relations.

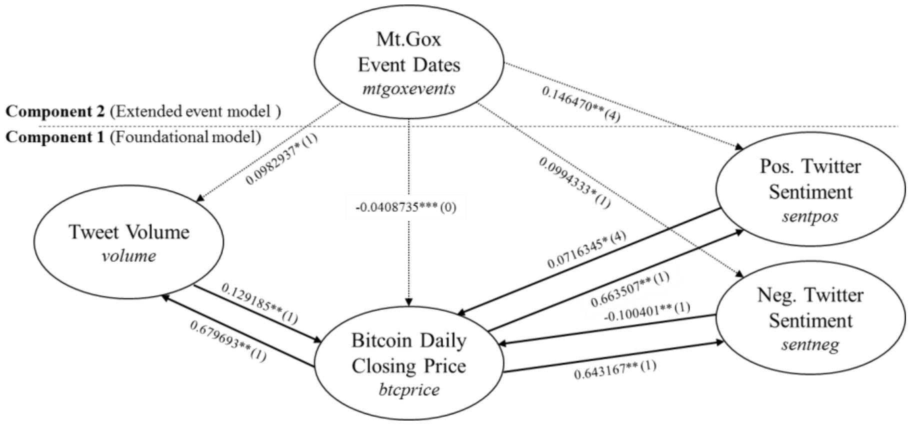

Figure 5. Variable Model with significant relationships

In our model component 1, we discovered the cointegration of all endogenous time series and found a significant impact of positive Twitter sentiment, negative Twitter sentiment and tweet volume on the Bitcoin price, which we illustrate with the help of impulse response functions. However, we note that all these relationships are bidirectional, which means that changing Bitcoin prices also induce significant responses in the other time series. Except for positive Twitter sentiment, which is significant with a lag of 4, all discovered impact-response relations are significant with a lag of 1, meaning that they start to become manifest on the day after a selloff event. In our model component 2, we observed significant unidirectional impact-response relations between *mtgoxevents* and all endogenous time series. Here, we discovered the impact on Bitcoin performance being the most immediate and consistent one over the course of six days after the event. The impact on the other endogenous time series varies considerably more in the time dimension but still reveals plausible and significant results for some lags.

Overall, our research provides the following theoretical contributions. First, we propose a distinct methodology to perform event studies in the field of cryptocurrencies. This approach can be adapted by using models other than VECM and is subject to be validated by further research. We extend current literature by applying an event study method, which is widely used in the capital market context, on the crypto market. Further, our research implies several practical implications. We provide investors with a viable and sound approach to anticipate price movements based on Twitter data. One could derive from our findings that shorting Bitcoin in case of a Mt.Gox selloff event is beneficial in the short run, however further investigation is required. Further, our research approach and results are particularly helpful and important for regulatory institutions as it can serve as an important building block towards governance mechanisms of cryptocurrencies. This is especially relevant in the context of potential price manipulation with social bots, a phenomenon whose existence we cannot rule out.

We acknowledge limitations that represent promising starting points for further research. First, we investigated the Bitcoin price performance in the context of Mt.Gox selloff events, but did not take into account other external effects such as price movements due to hype cycles. Second, the approach of dynamic event window determination based on moving average indicators can be seen critically, as there is no unambiguous evidence of the respective window lengths being adequate. Third, our analysis of dynamic relationships between Twitter data and Bitcoin might be extended with additional variables, as we only incorporated four time series. Future research on event study sensitive topics would be encouraged to consider additional dimensions that affect the trading behaviour of investor in general, which could range from technology-related to economic factors. Future research might also consider a wavelet-coherence analysis given the complex and dynamic nature of both, social media metrics and Bitcoin market measures.

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