# Intraday liquidity and trading dynamics around extreme price movements in cryptocurrencies

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**Abstract**

Covering the 8 most widespread cryptocurrencies in the world across the 16 most active trading platforms from May 2015 to July 2018, we show that intraday extreme price movements (EPMs) in cryptocurrencies are accompanied by a sharp increase in trading volume, spreads and depth. This holds true whether we focus on the Bitcoin on the most active Bitfinex platform only, or extend the analysis across several cryptocurrencies and platforms. Using the logistic regression framework adapted to rare events, we show that the number of trades is the most consistent driver of EPMs, as it is often the case for traditional markets. However, the probability of an EPM varies significantly across platforms, as indicated by the high significance of time-invariant unobservable platform fixed effects. All in all, we expect further platform consolidation but we do not find evidence of obvious market dysfunction when prices move very sharply.

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# 1. Introduction

Over the last two decades, technological change in finance has been profound and the rise of cryptocurrencies has contributed to it by allowing for a new digital form of payment. Among these cryptocurrencies, bitcoin (BTC) is the most famous. Transaction are recorded in a register called the *blockchain* and the supply is deterministically fixed. There is no central counterparty as it is the case with a central bank that chooses the quantity of money in circulation. By solving cryptographic problems, miners ensure the stability of the network and are rewarded with cryptocurrencies in exchange of their service. Cryptocurrencies are traded 24/7, against other cryptocurrencies or traditional currencies, such as USD, EUR, JPY, or CNY.

A number of derivatives were created, such as the introduction of a tracker by NASDAQ OMX in May 2015 and two futures by CBOE and CME in December 2017. TeraExchange even proposes forwards on bitcoins. The development of these derivatives is an important milestones on Bitcoin's way to legitimacy. However, there is still a vivid debate among both scholars and practitioners on whether cryptocurrencies can reshape the financial system or even play any role as financial assets. Shutdowns of both platforms (such as MtGox) and websites accepting bitcoins (such as Silk Road) question the reliability of the whole system.

In that context, investors should care about both their potential capital gains *and* losses. Cryptocurrencies can indeed lose a significant part of their value in a very short time. For example, Bitcoin plummeted 18% on March 10 2017 following SEC's denial to launch an ETF. According to Thies and Molnár (2018), daily returns can vary from -48.52% to +40.14%. It is therefore of interest to better understand what triggers these extreme price movements (EPMs) since there is no bright future for cryptocurrencies without further market stability.

Although the growing popularity of cryptocurrencies have attracted the attention of academics, regulators, and central banks (Ali et al., 2014; McLeay et al., 2014), we still know close to nothing about the liquidity and trading dynamics on these markets when conditions are extreme. To the best of our knowledge, there is no study aiming at identifying evidence of market dysfunction when we zoom in on EPMs.

We look for evidence of market dysfunction by looking at what happens around EPMs in terms of liquidity and trading dynamics. We analyze how prices recover and aim to identify the drivers of EPMs. We start our analysis with the Bitcoin traded on the Bitfinex platform. Then, we extend the analysis by considering the 8 most widespread cryptocurrencies in the world across the 16 most active trading platforms. We perform both an event-study and a multivariate logistic regression analysis.

We show that EPMs in cryptocurrencies are accompanied by a sharp increase in trading volume, spreads and depth. This holds true whether we focus on the Bitcoin on the most active Bitfinex platform or extend the analysis to a multi-platform and a multi-cryptocurrency analysis. Using the logistic regression framework adapted to rare events, we show that the number of trades is the most consistent driver of EPMs, as it is often the case for traditional markets. However, the probability of an EPM varies significantly across platforms, as indicated by the high significance of time-invariant unobservable platform fixed effects. All in all, we expect further platform consolidation but we do not find evidence of obvious market dysfunction when prices move very sharply.

The remainder of the paper is as follows. In the next section, we review the relevant literature. Section 3 contains a description of our data and variables. In Section 4, we explain our methodology and report our empirical findings. In Section 5, we carry some robustness checks. Section 6 concludes.

## 2. Literature review

As far as cryptocurrencies are concerned, the financial academic literature is emerging. Still, we can regroup most studies into some major research questions. To name a few, are cryptocurrencies currencies or do they belong to another asset class? Do cryptocurrencies have an intrinsic value? Can we model cryptocurrencies' volatility? What are the consequences of adding cryptocurrencies to a traditional portfolio? Is there any price discovery across exchanges? Can we explain cryptocurrencies' returns? Besides these major research questions, some papers also look at transaction costs (Kim, 2017; Easley et al., 2019), the introduction of the futures (Corbet et al., 2018), the unethical activities associated to Bitcoin (Gandal et al., 2018), the construction of a reliable index (Trimborn and Härdle, 2018), trading strategies using machine learning algorithms (de Souza et al., 2019; Fischer et al., 2019), the multifractality of Bitcoin[1], etc.

First, it is important to determine whether Bitcoin, and cryptocurrencies in general, are currencies, commodities, or a different class of asset.[2] This has implications when comparing cryptocurrencies to other asset classes. It is generally accepted that a money should have three functions, i.e. medium of exchange, store of value, and an unit of account (Ali et al., 2014). Glaser et al. (2014) document that Bitcoin users are rather interested in a new speculative instrument than in a system of payment. Rogojanu and Badea (2014) discuss the various attempts of alternative

[1]References include da Silva Filho et al. (2018), Fang et al. (2018), Lahmiri and Bekiros (2018) and Takaishi (2018).

[2]If we consider BTC as a currency, then its relationship with traditional currencies should be seen as an exchange rate. However, if we consider BTC as an asset or a commodity, then it has a price.

currencies through history and how Bitcoin relates to these other currencies. Dyhrberg (2016a, p. 85) considers BTC as *'something in between gold and the American Dollar on a scale from pure medium of exchange advantages to pure store of value advantages'*. Ali et al. (2014, p. 278) note that *'in contrast to commonly used forms of money such as banknotes or bank deposits, digital currencies are not a claim on anybody. In this respect, they can therefore be thought of as a type of commodity. But unlike physical commodities such as gold, they are also intangible assets, or digital commodities.'* According to Baur et al. (2018), Bitcoin is a speculative instrument. To date, this debate is still ongoing although there are more and more evidence that Bitcoin is used as a speculative asset, without any utility as a medium of exchange.

Some authors have questioned the intrinsic value of bitcoin. Cheah and Fry (2015) document that Bitcoin's fundamental value is zero as they find evidence of a bubble between January and November 2013. Donier and Bouchaud (2015, p. 2) note that *'the absence of any compelling way to assess the fundamental price of Bitcoins makes the behavioral hypothesis highly plausible'* to explain market crashes. Therefore, this question is also closely related to the presence of a bubble in cryptocurrency markets. Corbet et al. (2018) and Chaim and Laurini (2019) analyze whether there are some bubbles. We discuss this point in Section 4.4.

A stream of literature investigates how to model cryptocurrencies' volatility. Indeed, cryptocurrencies' volatility is high in comparison with other financial assets. Dwyer (2015) notes that Bitcoin exhibit higher volatility than currencies on average. Bouoiyour and Selmi (2015a) analyze Bitcoin price from December 2010 to June 2015. They use Threshold-GARCH (TGARCH) and Exponential GARCH (EGARCH). Bouoiyour et al. (2016) study Bitcoin volatility from December 2010 to July 2016. According to these authors, although volatility decreases in the second part of the sample, Bitcoin is still not a mature market. They use several GARCH-related models and discriminate among the models with information criteria. Dyhrberg (2016a) uses GARCH and EGARCH models. To date, there is no consensus on which GARCH model best works. The sample period and/or the sample of cryptocurrencies under scrutiny is one possible explanation for these divergences of results.

While the analysis of cryptocurrencies' volatility on its own is interesting, it is also worth investigating whether this volatility translates to other asset classes. Trabelsi (2018) constructs a spillover index to measure to what extent cryptocurrencies are related to other asset classes, and finds that there is no spillover from cryptocurrency to other assets classes. If cryptocurrencies are unrelated to traditional asset classes, then it makes them useful with respect to portfolio management. Indeed, cryptocurrencies have been proposed as a new asset class to improve the risk-return trade-off in portfolio management. Cryptocurrencies are sometimes considered, rightly or wrongly, as the new gold (Dyhrberg, 2016a,b; Baur et al., 2018; Klein et al., 2018; Al-Yahyaee et al., 2019). According to Dyhrberg (2016b) and Corbet et al. (2018), bitcoin exhibits low correlation with other asset classes, which makes it attractive for portfolio management. Briere et al. (2015) find that including Bitcoin in a diversified portfolio enhances the portfolio's performance. However, Bouoiyour and Selmi (2015b, p. 449) indicates that *'there is no sign of Bitcoin being a safe haven.'* On the contrary, the same authors in a different study mention that Bitcoin is a safe haven because of the system anonymity, which questions the relevance of their conclusions. Looking at the correlations across cryptocurrencies, Canh et al. (2019) show that the correlations are quite high, implying that it is difficult to diversify a portfolio composed only with cryptocurrencies.

Cryptocurrency markets are highly fragmented. In that context, some authors study whether a specific platform has an informational advantage in comparison to the others. Brandvold et al. (2015) analyze the price discovery across 7 platforms between April 2013 and February 2014 and find that Mt.Gox and BTC-e, which had an important market share at that time, drive Bitcoin price the most. Since Mt.Gox shut down in the meantime, it is important to look at the cross-platforms dynamics. However, he notes that the information share strongly evolves over time. Ciaian et al. (2018) analyse 17 cryptocurrencies and find that while in the short-run cryptocurrencies' price are related, this effect decreases in the long-term.

Some studies look at cryptocurrencies returns. Financial assets exhibit non-normal returns and this stylized fact has been widely documented in the literature. The same applies to cryptocurrencies and this non normality is even more pronounced. Among 15 potential candidates, Chu et al. (2015) find that the generalized hyperbolic distribution to fit Bitcoin returns is the best statistical parametric distribution, while the normal distribution performs the worst. Using a Bayesian change point analysis, Thies and Molnár (2018) identify 48 structural breaks between September 2011 and August 2017 in Bitcoin returns. Cryptocurrency markets efficiency is assessed through various statistical tests on the returns, most often by testing the random walk hypothesis (Brauneis and Mestel, 2018; Aggarwal, 2019) or the adaptive market hypothesis (Khuntia and Pattanayak, 2018). Urquhart (2016) and Nadarajah and Chu (2017) disagree as to whether Bitcoin markets are efficient, with the divergence coming from the fact that Nadarajah and Chu (2017) use a power transformation before performing the efficiency tests. According to Al-Yahyaee et al. (2018), Bitcoin is less efficient than other traditional assets such as stocks, currencies, or gold. According to Tiwari et al. (2018), the market is efficient. Several studies note that inefficiency is evolving over time, making cryptocurrencies more mature (Khuntia and Pattanayak, 2018; Vidal-Tomás and Ibañez, 2018). Other forms of market (in)efficiency have been investigated such as price inconsistencies (Pieters and Vivanco, 2017), price clustering (Urquhart, 2017) or price bias Aloosh and Ouzan (2019).

If markets are not efficient however, then it should be possible to find factors that consistently allow investors to earn positive returns. Research in this area has been relatively important. Two types of factors have been proposed in the literature, i.e. economic factors, as other financial assets, and technological factors, that can be specific to the blockchain infrastructure. Bitcoin returns are related to macroeconomic fundamentals such as the global financial stress index (Bouri et al., 2018), economic policy uncertainty (Demir et al., 2018; Fang et al., 2019), CBOE VIX (Kjærland et al., 2018; Aalborg et al., 2019), global geopolitical risk index (Aysan et al., 2019). Baek and Elbeck (2015) and Liu et al. (2019) do not find any relationship between economic fundamentals and Bitcoin returns. They document that these returns are therefore a consequence of participants' activity. Among the technological factors, Kjærland et al. (2018) find that the hashrate does not help in modeling bitcoin price. Kristoufek (2013) finds bidirectional relationships between bitcoin price and Internet metrics, i.e. Google Trends and Wikipedia. Garcia et al. (2014) also show that search attention (Google Trends) and the number of new bitcoin users help explain the variation of Bitcoin price. Urquhart (2018) use volume and volatility to explain what drives the attention of Bitcoin. Google Search volume Index (SVI) is a popular metric to gauge investors' attention and this proxy is used in the literature to predict cryptocurrency returns as well (Panagiotidis et al., 2018; Aalborg et al., 2019; Bleher and Dimpfl, 2019; Eom et al., 2019). Using a LASSO framework, Panagiotidis et al. (2018) find that, among 21 potential candidates, SVI and gold returns best explain bitcoin returns. Aalborg et al. (2019) find no significant relationship between returns and SVI.

Our work is mostly related to Donier and Bouchaud (2015), Chaim and Laurini (2018) and Chevapatrakul and Mascia (2019) as we are interested in explaining major price changes in cryptocurrency markets. Chevapatrakul and Mascia (2019) find evidence of investor overreaction when returns are in the extreme tails of their distribution. Most papers document the important returns observed within cryptocurrency markets. For example, Chevapatrakul and Mascia (2019, p. 373) note that *'a daily loss of around - 26% was observed between 17th and 18th December 2013 and a monthly gain of 171% was realised between October and November 2013'.* However, we extend these studies by providing an intraday and a cross-cryptocurrencies and cross-platforms analysis.

In this paper, we (i) analyze what are the intraday trading and liquidity dynamics around EPMs and (ii) identify the drivers of EPMs. Several empirical studies on cryptocurrencies use daily data based on prices and volume information only. As such, they do not bring any information on the intraday price dynamics, neither in the orderbook dynamics. In addition, most of these studies investigate the bitcoin only and/or over a short time period and/or before the 2017 bubble bursts. Our study does not suffer from any of these shortcomings.

## 3. Data

We obtain data from Kaiko, an independent data provider that collects data directly from the exchanges. The database is made of two distinct datasets. The first dataset records all the trades that occurred on each platform with date and time, price, number of cryptocurrencies exchanged, as well as a boolean variable indicating whether the trade is buyer- or seller-initiated. The second dataset contains minute-by-minute orderbook snapshots with bid/ask prices and quantities up to the $10^{th}$ limit.

The database includes 16 different exchanges on which BTCUSD is traded (i.e. Bitfinex, Bitflyer, Bitstamp, Bittrex, BTCC, BTCE, Cexio, Coinbase, Gatecoin, Gemini, Hitbtc, Huobi, Itbit, Kraken, OkCoin, and Quoine). Although the trade dataset starts in 2010, the earliest orderbook data provided dates back to May 2015. Therefore, we restrict our analysis to the period ranging from May 2015 to July 2018 for which we have both trade and orderbook information.

Table 1 presents the database. It shows the period for which we have access to orderbook information, the number of days, the number of observations, the daily average number of observations,[3] the total number of trades, and the daily average of trades. In Panel A, we report statistics for all the 16 platforms on which BTCUSD is traded. Figure 1 represents the monthly market share of each platform for BTCUSD from July 2010 to September 2018.[4] We observe that in the beginning of the period, there was a monopolistic situation held by MtGox. However, this platform shut down in February 2014, which resulted in a loss of more than 400 millions of dollars for its users according to Forbes.[5] At the end of our sample period, Bitfinex is the biggest platform in terms of trading activity with more than 38,000 trades per day, followed by Coinbase, Hitbtc, Huobi, and Bitstamp. In Panel B, we report the major cryptocurrencies traded against USD on the platform Bitfinex, i.e. Bitcoin Cash (BCH), Bitcoin (BTC), EOS (EOS), Ethereum (ETH), Litecoin (LTC), Stellar (XLM), Monero (XMR), and Ripple (XRP). Over the period, we have more than 260 million trades and more than 20 million orderbook snapshots.

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[3] We report this information as a proxy for data quality. This number should theoretically be equal to 1,440 as we should have one observation per minute. However, technical glitches or platform upgrades may affect this number. Some platforms may be temporarily down because of system upgrades or hacking events. At the end of the sample period, the data provider changed its frequency to 2,880 snapshots per day.

[4] Market share is determined by the relative proportion of trades on each platform.

[5] Source: `https://www.forbes.com/sites/cameronkeng/2014/02/25/bitcoins-mt-gox-shuts-down-loses-409200000-dollars-recovery-steps-and-taking-your-tax-losses/#41ba609d5c16`

Table 1: Data - Descriptive statistics

**Panel A: BTCUSD on all platforms**

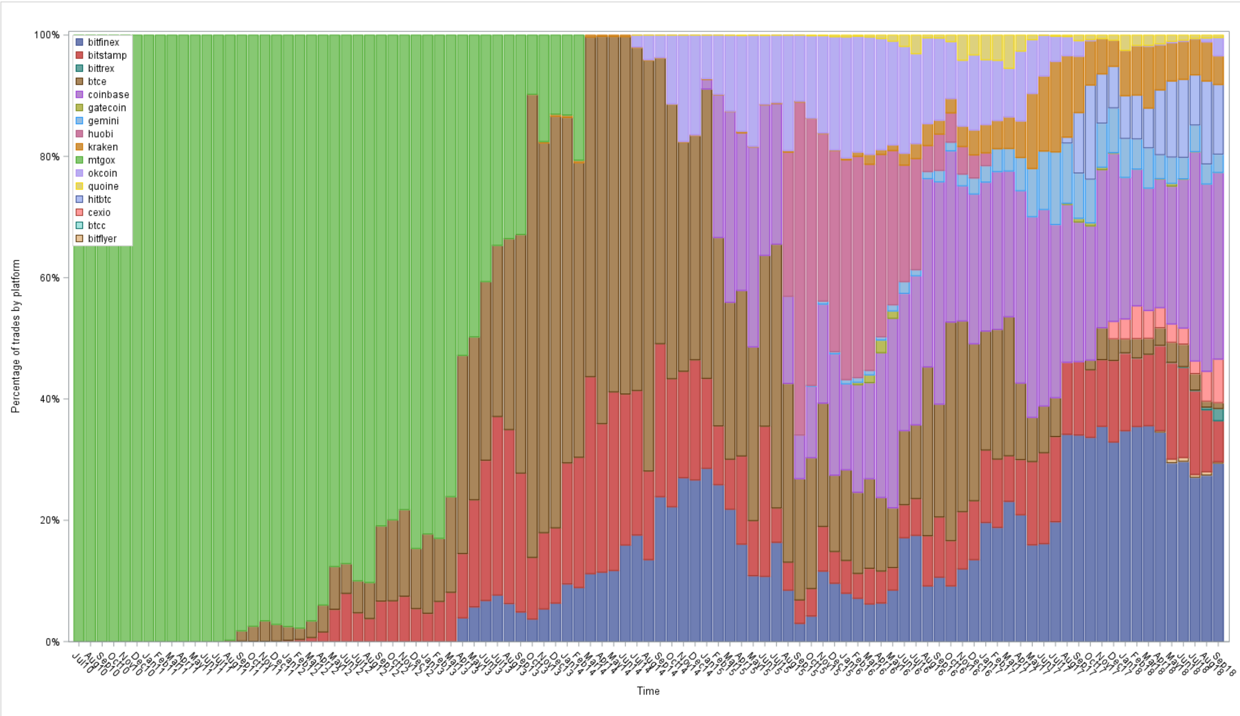
| Exchange | Start | End | Days (ND) | Obs (NO) | Daily avg obs (DANO) | Trades (NT) | Daily avg trades (DANT) |
|---|---|---|---|---|---|---|---|
| bitfinex | 15-May-15 | 21-Jul-18 | 1,163 | 1,537,507 | 1,322 | 45,133,393 | 38,808 |
| bitflyer | 18-Apr-18 | 21-Jul-18 | 94 | 239,226 | 2,545 | 109,869 | 1,169 |
| bitstamp | 15-May-15 | 20-Jul-18 | 1,162 | 1,521,183 | 1,309 | 19,608,226 | 16,875 |
| bittrex | 1-Jun-18 | 20-Jul-18 | 49 | 143,323 | 2,925 | 9,948 | 203 |
| btcc | 13-Feb-18 | 20-Jun-18 | 127 | 276,122 | 2,174 | 15,235 | 120 |
| btce | 15-May-15 | 21-Jul-18 | 1,163 | 1,397,452 | 1,202 | 16,288,069 | 14,005 |
| cexio | 11-Dec-17 | 20-Jul-18 | 221 | 442,639 | 2,003 | 2,885,221 | 13,055 |
| coinbase | 15-May-15 | 20-Jul-18 | 1,162 | 1,574,932 | 1,355 | 42,520,453 | 36,592 |
| gatecoin | 18-Feb-16 | 21-Jul-18 | 884 | 731,320 | 827 | 322,237 | 365 |
| gemini | 12-Oct-15 | 21-Jul-18 | 1,013 | 1,373,409 | 1,356 | 8,601,783 | 8,491 |
| hitbtc | 26-Aug-17 | 21-Jul-18 | 329 | 605,017 | 1,839 | 9,075,776 | 27,586 |
| huobi | 10-Nov-15 | 13-Sep-17 | 673 | 687,214 | 1,021 | 13,895,640 | 20,647 |
| itbit | 7-Oct-15 | 21-Jul-18 | 1,018 | 1,336,609 | 1,313 | 2,684,271 | 2,637 |
| kraken | 25-Aug-15 | 21-Jul-18 | 1,061 | 1,447,116 | 1,364 | 10,298,238 | 9,706 |
| okcoin | 15-May-15 | 21-Jul-18 | 1,163 | 1,566,039 | 1,347 | 10,403,684 | 8,946 |
| quoine | 22-Sep-16 | 21-Jul-18 | 667 | 948,031 | 1,421 | 2,127,941 | 3,190 |
| **TOTAL** | | | | **15,827,139** | | **183,979,984** | |

**Panel B: All cryptos against USD on Bitfinex**

| Crypto | Start | End | Days (ND) | Obs (NO) | Daily avg obs (DANO) | Trades (NT) | Daily avg trades (DANT) |
|---|---|---|---|---|---|---|---|
| bchusd | 10-Aug-17 | 21-Jul-18 | 345 | 615,299 | 1,783 | 9,982,619 | 28,935 |
| btcusd | 15-May-15 | 21-Jul-18 | 1,163 | 1,537,507 | 1,322 | 45,133,393 | 38,808 |
| eosusd | 10-Aug-17 | 21-Jul-18 | 345 | 636,848 | 1,846 | 12,757,782 | 36,979 |
| ethusd | 28-Apr-16 | 21-Jul-18 | 814 | 1,048,549 | 1,288 | 24,009,056 | 29,495 |
| ltcusd | 14-Sep-16 | 21-Jul-18 | 675 | 941,654 | 1,395 | 14,194,655 | 21,029 |
| xlmusd | 2-May-18 | 21-Jul-18 | 80 | 206,667 | 2,583 | 46,179 | 577 |
| xmrusd | 10-Aug-17 | 21-Jul-18 | 345 | 633,362 | 1,836 | 2,620,766 | 7,596 |
| xrpusd | 10-Aug-17 | 21-Jul-18 | 345 | 616,421 | 1,787 | 13,484,949 | 39,087 |
| **TOTAL** | | | | **6,236,307** | | **123,823,971** | |

This Table reports the start and the end of the period for which we have orderbook information, the number of days (ND), the number of observations (NO), the daily average number of observations (DANO), the total number of trades (NT), and the daily average of trades (DANT). In Panel A, we report all platforms on which BTCUSD is traded, and in Panel B, we report all the cryptocurrencies traded in USD in Bitfinex.

Figure 1: Market shares by platforms in BTCUSD trading from July 2010 to September 2018




This figure represents the platforms' monthly market share for BTCUSD from July 2010 to September 2018.

From the trade database, we compute the number of trades ($NT$), the quantities of cryptos traded ($QT$), the volume traded ($VT$), the average trade size ($ATS = QT/NT$), and the average trade volume ($ATV = VT/NT$). We also compute Amihud (2002)'s illiquidity measure:

$$Amihud_t = \frac{|R_t|}{VT_t} \tag{1}$$

where $R_t$ is the log-return during interval $t$. Cryptocurrencies are fairly new assets and these markets are not as mature as equity or forex markets. Therefore, we compute returns based on trade prices. While this approach may suffer from the bid-ask bounce, it better reflects the economic reality in terms of returns. Brogaard et al. (2018, p. 258) suggest that large price movements can be triggered by trade imbalances. Therefore, we measure the trade imbalance ($T\_Imb$) as:

$$T\_Imb_t = \frac{BUY_t - SELL_t}{BUY_t + SELL_t} \tag{2}$$

where $BUY_t$ ($SELL_t$) is the number of buyer-initiated (seller-initiated) trades during interval $t$. We do not have to use Lee and Ready (1991)'s algorithm since trades are signed in the database.

As proxies for liquidity, we compute the quoted spreads ($QS$), relative spreads ($RS$), depth at the best quotes ($DEPTH$) and at the 5 best quotes ($DEPTH5$) in monetary volume, orderbook imbalance at the best quotes ($OB\_Imb$) and at the 5 best quotes ($OB\_Imb5$), Slope ($Slope$) (Næs and Skjeltorp, 2006), and Dispersion ($Dispersion$) (Kang and Yeo, 2008):

$$QS = PA_1 - PB_1 \tag{3}$$

$$RS = 2 * (PA_1 - PB_1)/(PA_1 + PB_1) \tag{4}$$

$$DEPTH = (QB_1 + QA_1) \tag{5}$$

$$DEPTH\_DOLLAR = (PB_1 * QB_1) + (PA_1 * QA_1) \tag{6}$$

$$DEPTH5 = \sum_{j=1}^{5}(QB_j + QA_j) \tag{7}$$

$$DEPTH5\_DOLLAR = \sum_{j=1}^{5}((PB_j * QB_j) + (PA_j * QA_j)) \tag{8}$$

$$OB\_Imb = \frac{QB_1 - QA_1}{QB_1 + QA_1} \tag{9}$$

$$OB\_Imb5 = \frac{\sum_{j=1}^{5}(QB_j - QA_j)}{\sum_{j=1}^{5}(QB_j + QA_j)} \tag{10}$$

$$Slope = \frac{DE + SE}{2} \tag{11}$$

$$DE = \frac{1}{5}\left(\frac{\upsilon_1^B}{|PB_1/p_0 - 1|} + \sum_{j=1}^{4}\frac{\upsilon_{j+1}^B/\upsilon_j^B - 1}{|PB_{j+1}/PB_j - 1|}\right) \tag{12}$$

$$SE = \frac{1}{5}\left(\frac{\upsilon_1^A}{|PA_1/p_0 - 1|} + \sum_{j=1}^{4}\frac{\upsilon_{j+1}^A/\upsilon_j^A - 1}{|PA_{j+1}/PA_j - 1|}\right) \tag{13}$$

$$\upsilon_j^A = ln(QA_j) \tag{14}$$

$$\upsilon_j^B = ln(QB_j) \tag{15}$$

$$p_0 = \frac{PB_1 + PA_1}{2} \tag{16}$$

$$Dispersion = \frac{1}{2}\left(\frac{\sum_{j=1}^{n}\omega_{i,j,t}^B Dst_{i,j,t}^B}{\sum_{j=1}^{n}\omega_{i,j,t}^B} + \frac{\sum_{j=1}^{n}\omega_{i,j,t}^A Dst_{i,j,t}^A}{\sum_{j=1}^{n}\omega_{i,j,t}^A}\right) \tag{17}$$

with $QB_j$ ($QA_j$) the quantity available at limit $j$, $Dst_j^B = PB_{j-1} - PB_j$ and $Dst_j^A = PA_j - PA_{j-1}$. $PB_0$, $\omega_j^B$ ($\omega_j^A$) weights the $Dst_i^B$ ($Dst_j^A$), by the depth size at the $j^{th}$ limit on the total depth of the five best limits. For each hourly interval $t$, we compute the average and median values of these variables for each cryptocurrency/platform.

Brogaard et al. (2018, p. 253) ground their analysis on stressful periods and define them as *'unexpected and rapidly developing extreme price movements (EPMs) that belong to the* $99.9^{th}$ *percentile of the return distribution'*. We follow this approach by first computing absolute logarithmic returns based on the last observed trade price during the interval. While Brogaard et al. (2018) use 10-second intervals for stocks traded on NASDAQ, we take longer intervals, i.e. one hour, as cryptocurrencies markets are not traded at the same regularity and frequency, being much more immature than equity markets. We use the less conservative threshold of $99^{th}$ percentile in order to fix the number of EPMs to 1% in our sample. Because of the extreme volatility in cryptocurrencies' markets, the whole set of EPMs present in the $99^{th}$ percentile is large in magnitude. Brogaard et al. (2018) analyze two years of data on NASDAQ stocks and use a frequency of 10 seconds, resulting in more than 45 millions observations and 45,200 EPMs. In the case of BTCUSD on Bitfinex, using Brogaard et al. (2018)'s more conservative threshold of $99.9^{th}$, we identify 27 EPMs while this number moves to 275 in our case. To ease notation, we refer to returns exceeding the $99^{th}$ ($99.9^{th}$) percentile as $EPM_{99}$ ($EPM_{99.9}$). There are a few papers that look at extreme price movements in cryptocurrencies. Vidal-Tomás et al. (2019, p. 182) define *'extreme down (up) market as 5% of the lower (upper) tail of the market return distribution'*. Blau (2017) use the same threshold. Therefore, our threshold of 99% should identify more extreme events than the aforementioned studies.

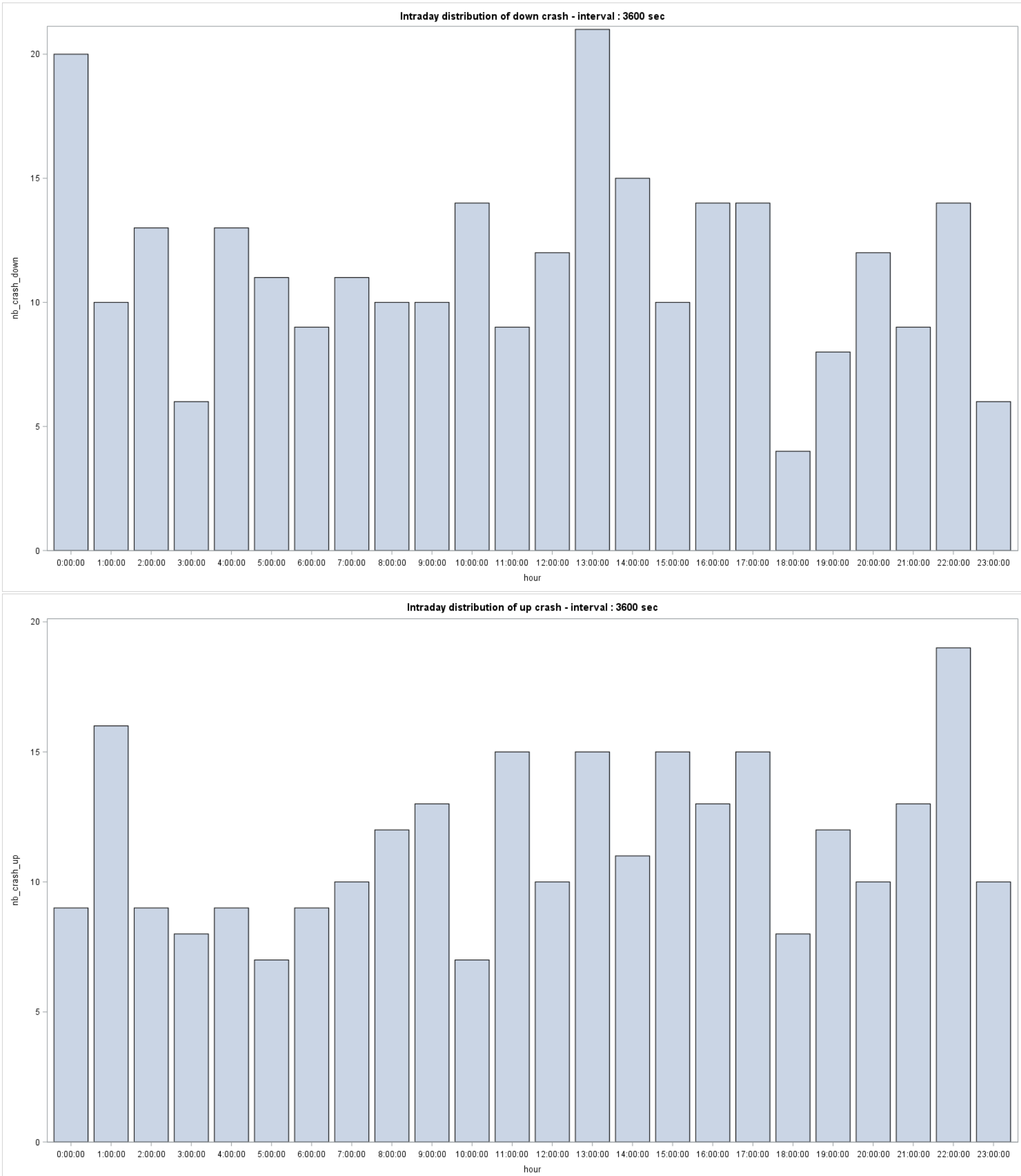
# 4. Empirical analysis

## 4.1. The case of BTCUSD on Bitfinex

We compute absolute log-returns over 3600 seconds at various percentiles, including the $99^{th}$ and $99.9^{th}$ percentiles. Consider the case of BTCUSD on the platform Bitfinex. An $EPM_{99}$ ($EPM_{99.9}$) occurs when the hourly absolute return exceeds 3.57% (6.97%). We identify 275 (27) $EPM_{99}$ ($EPM_{99.9}$) in BTCUSD on the platform Bitfinex. Figure 2 shows the distribution of EPMs across the day at the $99^{th}$ percentile. There is no clear clear intraday pattern in the occurrence of these EPMs over the day. We conjecture that the absence of intraday pattern is because Bitcoin markets are open 24/7. This result is in contraction with Brogaard et al. (2018) who find more EPMs at the beginning and at the end of the NASDAQ trading session. This is one of many stylized fact where cryptocurrencies depart from more traditional asset classes.

Table 2 compares the full sample of hourly returns with the sample of $EPM_{99}$. We report the mean and median values of Amihud ratio ($Amihud$), average trade size ($ATS$), average trade volume ($ATV$), depth at best quotes ($Depth$), depth at the 5 best quotes ($Depth5$), number of trades ($NT$), orderbook imbalance ($OB\_Imb$), orderbook imbalance at the 5 best quotes

Figure 2: Intraday distribution of EPMs in BTCUSD on the platform Bitfinex




These figure represent the intraday distribution of EPMs in BTCUSD at the 99th percentile on Bitfinex. We separate the graphs between negative EPMs (down crashes, top) and positive EPMs (up crashes, bottom).

($OB\_Imb5$), relative spread ($RS$), quoted spread ($QS$), quantities traded ($QT$), absolute trade imbalance ($Abs\_T\_Imb$)[6], and volume traded ($VT$). We test whether these differences are statistically significant across both subsamples, using Student's $t$-test on unstandardized data.

During EPMs, trading activity, measured either in number of trades, quantities traded, or monetary volume strongly increase by a factor of 5.8, 6.7, and 7.4, respectively. Each increase is statistically different from zero at the 1% level. While ATS does not change, ATV also strongly increases, from 1,679.40$ to 3,350.16$. The quoted and relative spreads also increase sharply during EPMs. While this is negative in terms of liquidity, we find that depth measures on the first limit or for the five best limits are also increasing. In essence, the cost for immediacy increases while many traders are present at both demand and supply side. This could mean that the traders acting during EPMs are rather patient and do not agree to pay the increased spread induced by the previous price rally or sell-off.

[6]We use trade imbalance in absolute value when EPMs are not separated between downward and upward EPMs. When the EPM direction is taken into account, we use trade imbalance.

Table 2: Descriptive statistics - BTCUSD on Bitfinex

| | Mean | Median | StDev. | N |
|---|---|---|---|---|
| **Panel A: Full sample** | | | | |
| *Trade-based variables* | | | | |
| $ATS$ | 1.3684 | 0.94 | 1.19 | 27,257 |
| $ATV$ | 1,679.40 | 1,229.77 | 1,295.42 | 27,257 |
| *Amihud* | $2.019E^{-8}$ | $4.336E^{-9}$ | $6.532E^{-7}$ | 27,158 |
| $NT$ | 1,603.36 | 513.00 | 2,599.95 | 27,661 |
| $QT$ | 1,078.69 | 576.79 | 1,498.22 | 27,661 |
| $VT$ | 5,125,542.00 | 522,850.50 | 11,433,054.00 | 27,661 |
| *Abs_T_Imb* | 0.2216 | 0.1714 | 0.1880 | 27,661 |
| *Orderbook-based variables* | | | | |
| *Abs_OB_Imb* | 0.1937 | 0.14422 | 0.1824 | 25,069 |
| *Abs_OB_Imb*5 | 0.1801 | 0.1417 | 0.1607 | 25,069 |
| *Depth* | 34,571.65 | 14,085.44 | 54,712.48 | 25,069 |
| *Depth*5 | 107,067.50 | 57,031.65 | 119,706.10 | 25,069 |
| $QS$ | 0.6105 | 0.2312 | 1.4868 | 25,069 |
| $RS$ | 0.0359 | 0.0249 | 0.1872 | 25,069 |
| **Panel B: Extreme price movements ($EPM_{99}$)** | | | | |
| *Trade-based variables* | | | | |
| $ATS$ | 1.2570 | 0.5587 | 1.4120 | 275 |
| $ATV$ | 3,350.16*** | 3,539.53 | 1,520.06 | 275 |
| *Amihud* | $1.046E^{-8}$ | $1.279E^{-9}$ | $4.414E^{-8}$ | 275 |
| $NT$ | 9,312.30 *** | 9,214.00 | 6,796.36 | 275 |
| $QT$ | 7,184.26*** | 5,644.42 | 6,551.86 | 275 |
| $VT$ | 38,008,423.00*** | 35,532,461.00 | 33,612,221.00 | 275 |
| *Abs_T_Imb* | 0.1402 | 0.1124 | 0.1082 | 275 |
| *Orderbook-based variables* | | | | |
| *Abs_OB_Imb* | 0.13549*** | 0.0864 | 0.1610 | 251 |
| *Abs_OB_Imb*5 | 0.1248 | 0.0876 | 0.1080 | 251 |
| *Depth* | 60,881.66*** | 51,103.14 | 62,855.32 | 251 |
| *Depth*5 | 215,201.80*** | 192,957.30 | 179,184.00 | 251 |
| $QS$ | 3.2403*** | 2.4000 | 3.0579 | 251 |
| $RS$ | 0.0724*** | 0.0465 | 0.0789 | 251 |

This Table reports descriptive statistics about Amihud ratio (*Amihud*), average trade size ($ATS$), average trade volume ($ATV$), depth at best quotes (*Depth*), depth at the 5 best quotes (*Depth*5), number of trades ($NT$), absolute orderbook imbalance (*Abs_OB_Imb*), absolute orderbook imbalance at the 5 best quotes (*Abs_OB_Imb*5), relative spread ($RS$), quoted spread ($QS$), quantities traded ($QT$), absolute trading imbalance (*Abs_T_Imb*), and volume traded ($VT$). All variables are defined in section 3. For each variable, we report the mean, median, standard deviation, and number of observations. Using a $t$-test, we test for the statistical differences between Panel A and Panel B. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

For each EPM, we analyze its percentage of recovery up to 24 hours after its occurrence. We report in Figure 3 the extent to which these EPMs recover over time. We distinguish between negative EPMs and positive EPMs. We observe an important disparity in terms of recovery.

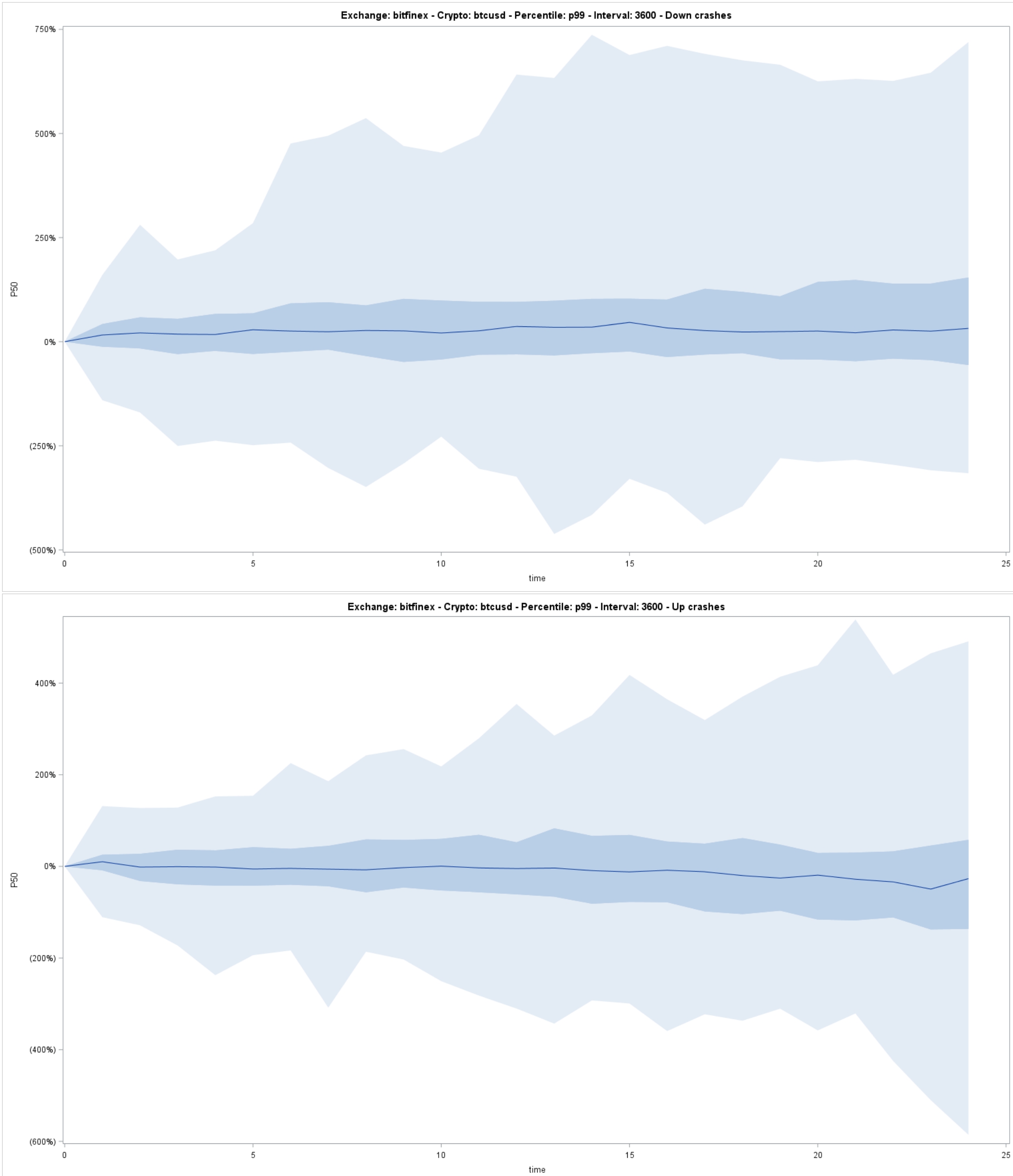
### 4.2. Event study

We first run an event study analysis in order to assess how market quality evolves around EPMs. To do so, we first standardize our market quality variables by exchange and by cryptocurrency, so that each variable has a mean of 0 and a standard deviation of 1. Our baseline analysis uses a window of 24 hours around the event, i.e. $t \in [-12; 12]$. We filter EPMs such that there is no other EPMs in the event window in order to prevent any contagion effect. In order to assess the significance of the intra-window pattern, we use the non-parametric signed rank test which performs relatively well in comparison with standard parametric tests and presents the advantage of not requiring any particular assumption on the shapes of the distributions (Corrado, 2011, p. 213).

Figure 4 shows the dynamics of the relative spread around downward EPMs (upper chart) and upward EPMs (lower chart). The event window includes 12 observations before the event, the event, and 12 observations after the event. Squares (□), circles (○), and triangles (△) indicate rejection of the null hypothesis of the signed rank test at the 1%, 5%, and 10% confidence levels, respectively. The results highlight a very interesting fact. At the time of a downward EPMs, the spread increases significantly and remains significantly high for the next two hours. This suggests that (1) liquidity demanders become aggressive and sell at the ask price or submit market order in order to ensure that their position is closed, or that (2) liquidity providers vanish from the market at that moment because they fear that they will trade with a better informed trader.

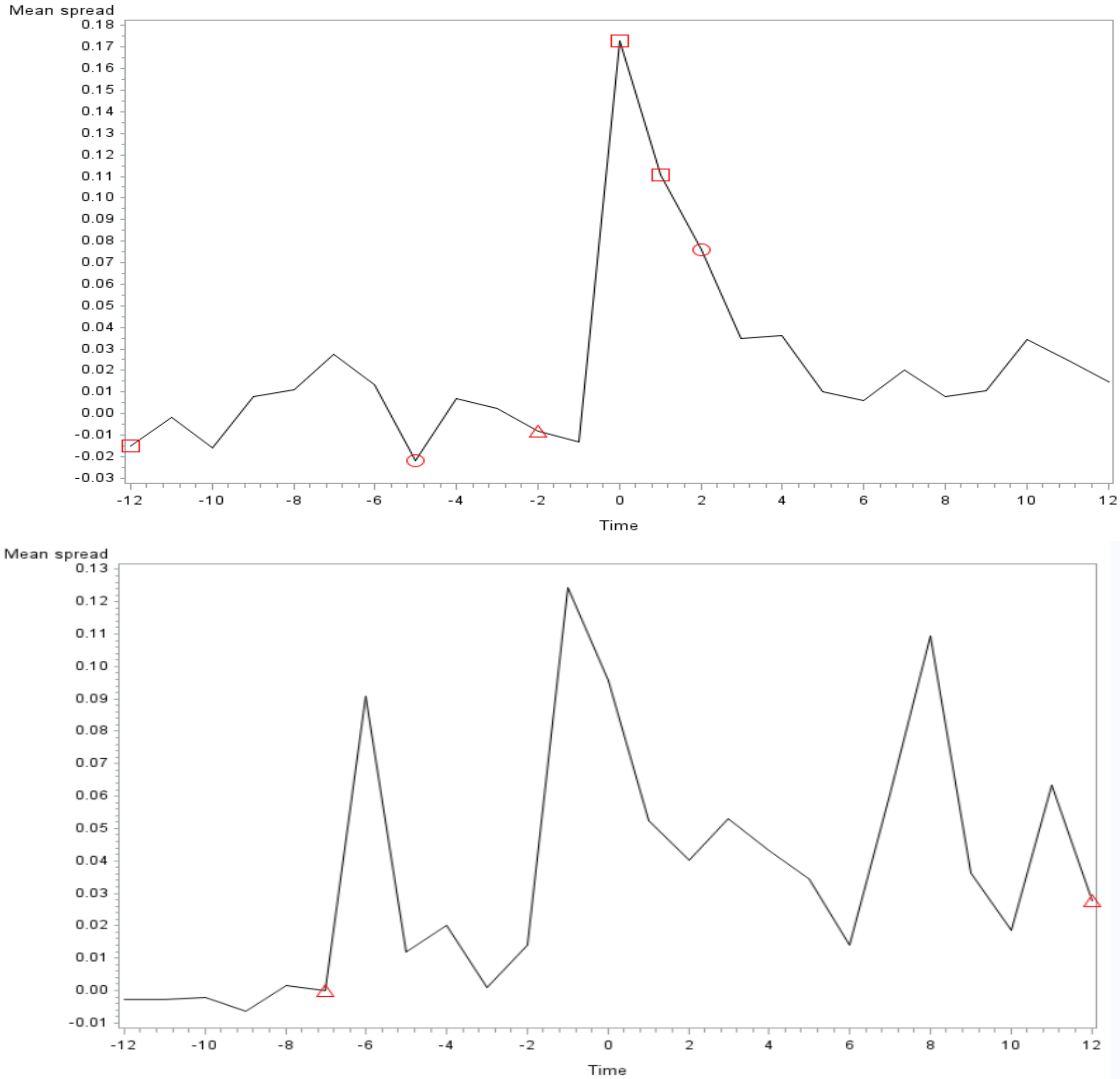
Similarly to Brogaard et al. (2018), we also look at the trading imbalance around EPMs. We

Figure 3: Percentage of price recovery after an EPM in BTCUSD on the platform Bitfinex




These figures represent the percentage of recovery conditionally on time, up to 24h after an EPM in BTCUSD on the platform Bitfinex. We represent the median value, a confidence band between the $25^{th}$ and the $75^{th}$ percentile and the confidence band between the minimum and the maximum recovery. We separate the graphs between negative EPMs (down crashes, top) and positive EPMs (up crashes, bottom).

Figure 4: Event study - relative spread




This figure shows the dynamics of the relative spread around downward EPMs (upper chart) and upward EPMs (lower chart). The event window includes 12 observations before the event, the event, and 12 observations after the event. Squares (□), circles (○), and triangles (△) indicate rejection of the null hypothesis at the 1%, 5%, and 10%, respectively.

find that there is a strong imbalance during the interval of the EPM. Figure 5 shows the dynamics of trading imbalance around downward EPMs (upper chart) and upward EPMs (lower chart). There is a strong negative (positive) imbalance during down (up) crashes. This evidence highlights that EPMs are triggered by traders' trading activity. Accordingly, a positive (negative) imbalance, i.e. a buying (selling) pressure drives prices up (down). Therefore, this is line with economic intuition, and cryptocurrency markets seem to work as *'traditional markets'* in this regard. This result is also in line with Donier and Bouchaud (2015) who provide evidence of strong order flow imbalance during market crashes.

### 4.3. Addressing the drivers of EPMs

In this section, we investigate the drivers of the occurrence of EPMs. We first build our dependent variable, $EPM_{99,i,j,t}$, as a dummy variable which equals 1 when there is an EPM at time $t$, and 0 otherwise. Since the dependent variable is a binary response variable, we implement a logistic regression framework (LOGIT) in order to address the determinants of the occurrence of EPMs, while appropriately fitting the response in [0,1]. Our model is specified as follows:

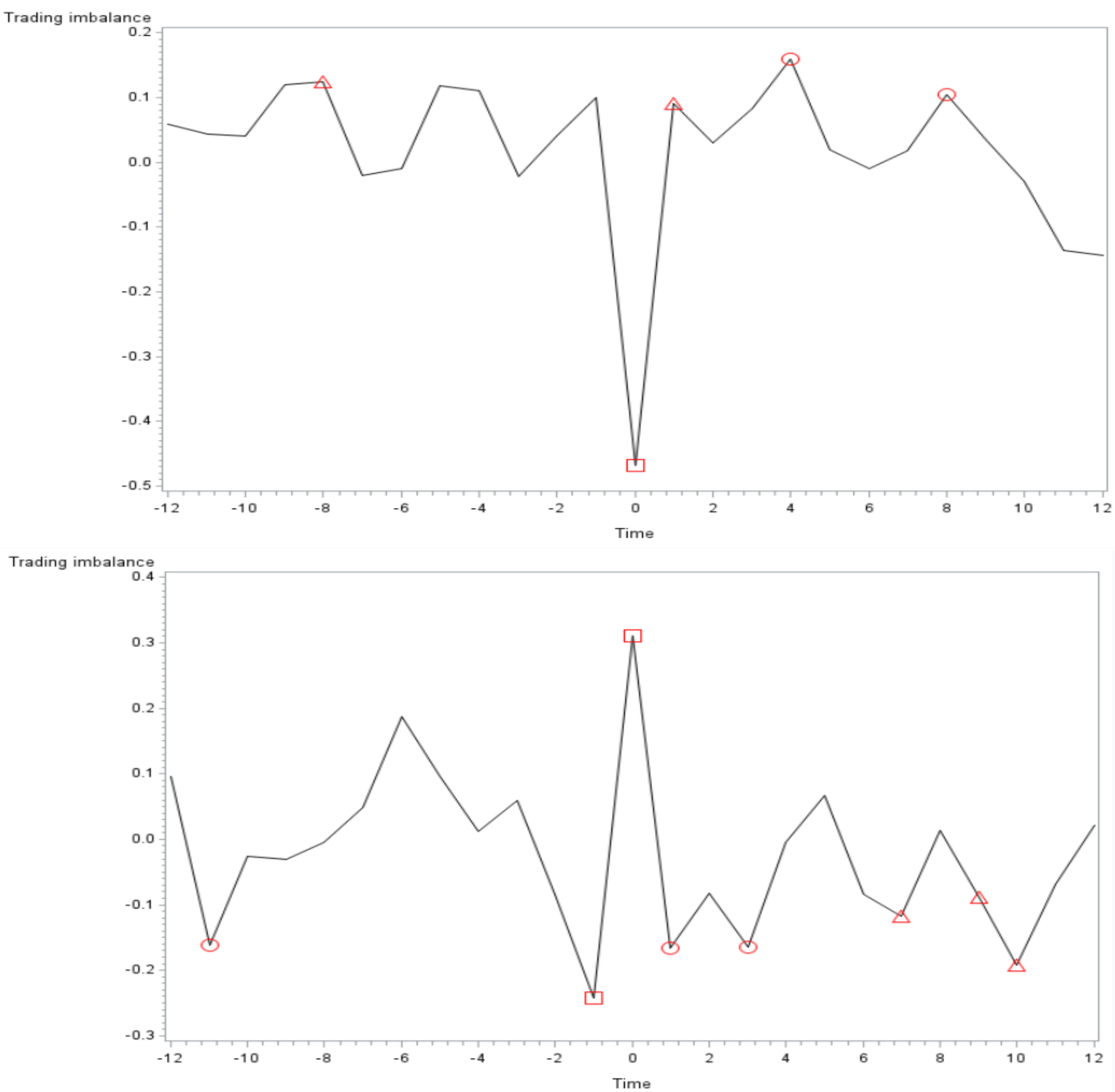
$$Prob(EPM_{99,i,j,t} = 1 | \boldsymbol{x'_{i,j,t-1}} \boldsymbol{\beta}, \alpha_i, \alpha_j) = \frac{exp(\boldsymbol{x'_{i,j,t-1}} \boldsymbol{\beta} + \alpha_i + \alpha_j)}{1 + exp(\boldsymbol{x'_{i,j,t-1}} \boldsymbol{\beta} + \alpha_i + \alpha_j)} \tag{18}$$

with

$$\boldsymbol{x'_{i,j,t-1}} \boldsymbol{\beta} = \alpha_0 + \beta_1 NT_{i,j,t-1} + \beta_2 Abs\_T\_Imb_{i,j,t-1} + \beta_3 R_{i,j,t-1} + \beta_4 RS_{i,j,t-1} + \epsilon_{i,j,t-1} \tag{19}$$

where $EPM_{99,i,j,t}$ is the occurrence of an EPM at time $t$ for platform $i$ and cryptocurrency $j$.

Figure 5: Event study - trading imbalance



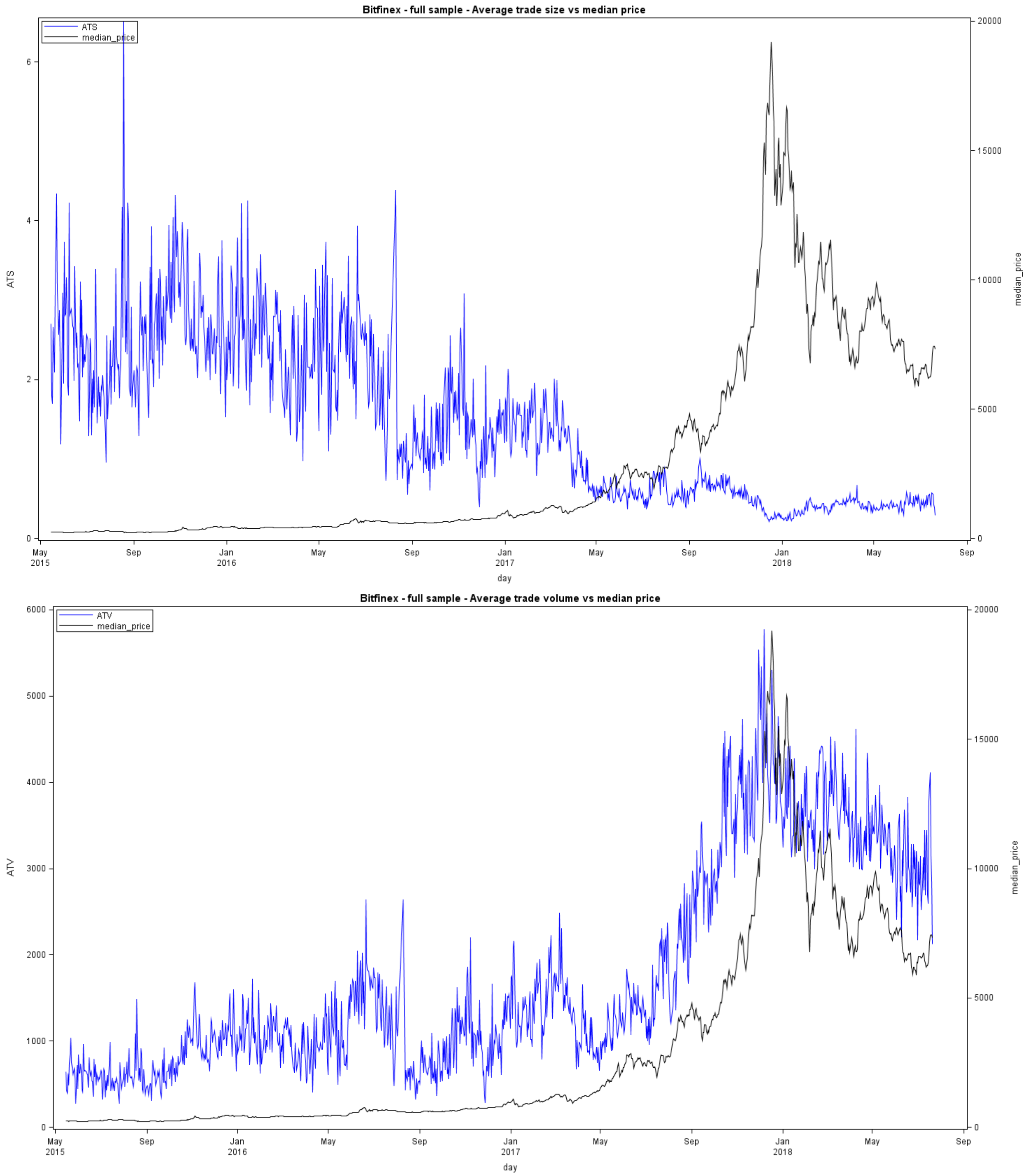

This figure shows the dynamics of the trading imbalance around downward EPMs (upper chart) and upward EPMs (lower chart). The event window includes 12 observations before the event, the event, and 12 observations after the event. Squares (□), circles (○), and triangles (△) indicate rejection of the null hypothesis at the 1%, 5%, and 10%, respectively.

The selection of explanatory variables included in the logistic regressions is based on Brogaard et al. (2018). We include the number of trades ($NT$), the absolute trading imbalance ($Abs\_T\_Imb$), the absolute log-return ($R$), and the relative spread ($RS$), plus an intercept. All these non-dummy variables are standardized and lagged by one period. $\alpha_i$ and $\alpha_j$ denote the fixed effects for platform $i$ and cryptocurrency $j$, respectively. Brogaard et al. (2018) use a measure of high frequency trading activity, $HFT^{NET}$, that is irrelevant in our setting. We replace this variable by a measure of trading imbalance. We use the number of trades instead of the share volume. The number of bitcoin traded is closely related to its price level, as we illustrate in Figure 6.[7] The number of trades is less impacted by this price effect since it is possible to trade fractions of cryptocurrencies. Investigating the relationship between trades and returns, Koutmos (2018) indicates that a one-standard shock deviation in transaction leads to an increase in return of 0.30%. We deliberately restrict the choice of explanatory variables to market-based variables. However, Chaim and Laurini (2018) indicate that hacking events or fork attempts may also be related to negative price jumps.

Two main sample-related issues are with this logistic specification in our specific case. First, the nature of EPMs in our definition generates a huge disequilibrium between events and non-events. For a LOGIT specification to be unbiased, a balanced proportion of events and non-events is required. EPMs are on the contrary rare events. Second, the inclusion of fixed effects in the maximum likelihood function yields inconsistent estimates. The issue that induces the bias, i.e., the incidental parameter problem, has been extensively discussed in the literature (Neyman et al., 1948; McFadden, 1973; Chamberlain, 1980). It comes from the fact that fixed effects do not disappear from the differentiated likelihood function in non-linear frameworks. To address the first bias, we

[7] As indicated in Figure 6, both variables are strongly correlated with BTCUSD price. Over the sample period, we measure a correlation of -0.52 (0.81) between $ATS$ ($ATV$) and price.

Figure 6: ATS and ATV versus price




These figures represent the relationship between the daily median price (black line) and the average trade size (ATS, blue line) (above) and between the daily median price (black line) and the average trade volume (ATV, blue line) from May 2015 to July 2018.

rely on Firth (1993) and implement a penalized maximum likelihood estimation, which was initially designed to deal with cases of separation.[8]

In the case of the above-mentioned logistic model, the different parameter estimates $\beta_k$ ($k = 1, ..., 4$) are the solutions of the partial differential score equations $\partial logL/\partial\beta_k \equiv U(\beta_k) = 0$, with $log\ L$ being the loglikelihood function. Firth (1993) proposes to correct the score equations for small sample bias, which generate quasi-complete separation, i.e., one regressor almost perfectly categorises events and non-events.

In the case of a general logistic model, the score equation for the parameter estimate $\beta_k$ is specified as:

$$U(\beta_k)* = \sum_{i=1}^{n}[y_i - \pi_i + h_i(1/2 - \pi_i)]x_{ik} = 0, \tag{20}$$

where $h_i$ are the $i$th diagonal elements of the H matrix $H = W^{1/2}X(X^TWX)^{-1}X^TW^{1/2}$ and $W = diag\pi_i(1 - \pi_i)$ is the weighting matrix. We implement this estimation method to our logistic regression framework.

The second issue, i.e., the presence of fixed effects, is less important in our case. This bias is heavily influenced by the number of data points per individual. In our case, since the number of time intervals, $t$, is large and the number of individuals $i$ ($j$), i.e. the number of platforms (cryptocurrencies) is small, the bias generated can be neglected (Mazza, 2019; Katz, 2001; Greene, 2004; Coupé, 2005).

We first implement the model stated in Equation 18 on one single cryptocurrency, BTCUSD, and one single platform, Bitfinex. Table 3 presents the results. $N$ is the total number of observations

[8] Interested readers should refer to Heinze and Schemper (2002) and Heinze (2006).

while $N_{y=0}$ ($N_{y=1}$) is the number of non-events (events). The odds ratio's (OR) are also reported.

Table 3: Bitfinex on BTCUSD

| | Coeff. | OR | $P$-value |
|---|---|---|---|
| $\alpha_0$ | -5.1118 | 0.0060 | *** |
| $NT_{t-1}$ | 0.4255 | 1.5303 | *** |
| $Abs\_T\_Imb_{t-1}$ | -0.5102 | 0.6004 | *** |
| $R_{t-1}$ | 0.1950 | 1.2153 | *** |
| $RS_{t-1}$ | 0.0339 | 1.0344 | ** |
| $N$ | 25,175 | | |
| $N_{y=0}$ | 24,925 | 99.01% | |
| $N_{y=1}$ | 250 | 0.99% | |
| $R^2$ | 1.62% | | |

This Table reports results of Equation 18. The dependent variable is the occurrence of an EPM at time $t$ and the independent variables include an intercept, the number of trades ($NT$), the absolute trade imbalance ($Abs\_T\_Imb$), the absolute return ($R$), and the relative spread ($RS$). All variables, excepting the intercept, are lagged by one period and are standardized. We estimate a LOGIT regression with Firth (1993)'s correction and where confidence intervals are computed based on the profile penalized log likelihood. We also report the R-squared. The odds ratio (OR) is the exponential of the coefficient estimate. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

We find that the 4 variables are statistically significant, at least at the 5% level. The number of trades, return, and relative spread display a positive coefficient, implying that an increase in these variables leads to a higher probability of an EPM occurrence. Among them, the number of trades has the biggest coefficient, 0.4255, and therefore the strongest impact. As our variables are standardized, we may interpret this parameter estimates as follows: a one-standard deviation increase in the number of trades, in return, and in the relative spread, increases the odds of having an EPM in the following period by 53.03%, 21.53%, and 3.44%, respectively. Finally, the absolute trading imbalance displays a negative coefficient and an odds ratio of 0.6004, thereby implying that a one-standard deviation increase in the absolute trading imbalance leads to a decrease in the odds of having an EPM in the following period by 39.96%.

While Bitfinex is the most important platform in terms of trading activity, it represents less than

25% of the trades for BTCUSD. As indicated in Table 1, there are 15 other platforms in our sample where BTCUSD is exchanged. This table also shows that there are many other cryptocurrencies. To take the dynamics across cryptocurrencies and across platforms into account, we estimate Equation 18 without restricting it to one platform and one cryptocurrency. All non-dummy variables are standardized at the cryptocurrency-level. Results are depicted in Table 4.

Table 4: LOGIT - All platforms - All cryptocurrencies

| | Coeff. | OR | $P$-value | Coeff. | OR | $P$-value |
|---|---|---|---|---|---|---|
| $\alpha_0$ | -4.9084 | 0.00738 | *** | -4.9754 | 0.0069 | *** |
| $NT_{t-1}$ | 0.2513 | 1.28573 | *** | 0.2592 | 1.2959 | *** |
| $Abs\_T\_Imb_{t-1}$ | -0.2606 | 0.77061 | *** | -0.2547 | 0.7751 | *** |
| $R_{t-1}$ | 0.3478 | 1.41599 | *** | 0.3438 | 1.4103 | *** |
| $RS_{t-1}$ | 0.1683 | 1.18333 | *** | 0.1726 | 1.1885 | *** |
| $\alpha_i$ | NO | | | YES | | |
| $\alpha_j$ | NO | | | YES | | |
| $N$ | 320,283 | | | 320,283 | | |
| $N_{y=0}$ | 317,050 | 98.99% | | 317,050 | 98.99% | |
| $N_{y=1}$ | 3,233 | 1.01% | | 3,233 | 1.01% | |
| $R^2$ | 1.33% | | | 1.34% | | |

This Table reports results of Equation 18. The dependent variable is the occurrence of an EPM at time $t$ and the independent variables include the number of trades ($NT$), the absolute trade imbalance ($T\_Imb$), the absolute return ($R$), and the relative spread ($RS$), platforms- and cryptocurrencies' fixed effects. All non-dummy variables are standardized at the platform-cryptocurrency-level. $N$ is the number of observations, $N_{y=0}$ ($N_{y=1}$) is the number of non-events (events). We also report the R-squared. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Again, we find that the number of trades display a positive and statistically significant coefficient at the 1% level. This result is consistent with Bouri et al. (2019) who find that trading volume Granger causes cryptocurrencies returns, even in the extreme tail of the distribution. Trading imbalance exhibits a negative coefficient, while return and relative spreads display positive and statistically significant coefficients. Accordingly, there seem to exist some early warnings, both in the orderbook and in the frequency of trades. The liquidity tends to deteriorate before, as spreads widen. We also estimate the same model without fixed effects and the conclusions are not affected

### 4.4. Pre-bubble, bubble, and post-bubble

Within its short history, Bitcoin experienced several phases of development. Bitcoin first exceeded the $1,000 gap in January 2017 (Corbet and Katsiampa, 2019). In 2017, BTC experiences a sharpe price increase, reaching almost 20,000$ in December 2017, before declining to approximately 3,000$ a year later. There are several empirical evidence of bubble presences in cryptocurrency markets (Bouri et al., 2019; Chen and Hafner, 2019; Chaim and Laurini, 2019; Ji et al., 2019).

We replicate our analysis on subsample periods, i.e. pre-, bubble, and post-bubble subsample periods, divided in accordance with Liu et al. (2019). Liu et al. (2019) use Phillips et al. (2011) and Phillips and Yu (2011)'s methodology to date the bubble of the Bitcoin and they separate their analysis according to the three following periods: pre-bubble (before May, 24 2017 - Panel A), bubble (between May, 25 2017 and January, 28 2018 - Panel B), and post-bubble (after January, 28 2018 - Panel C). We estimate Equation 18 on these three subsample periods. Accordingly, we standardize our variables with respect to these 3 periods. Results are presented in Table 5.

First, we notice a majority of EPMs, i.e. 130, occur during the bubble although this period is much shorter. Second, the number of trades and the relative spread always display positive and statistically significant coefficients. A one-standard deviation increase is the number of trades (the relative spread) increase the odds of observing an EPM by 24.30% (4.31%) before the bubble, by 80% (22.1%) during the bubble, and by 45.2% (78%) after the bubble. Third, the absolute trading imbalance displays a negative (and statistically significant) coefficient before the bubble. In the others subsamples, the variable is not statistically different from zero. The coefficient of the return is first positive, then non-significant, and finally negative, which questions the stability of this result.

Table 5: LOGIT - Bitfinex - BTCUSD - subsamples

| | Panel A | | | Panel B | | | Panel C | | |
|---|---|---|---|---|---|---|---|---|---|
| | Coeff. | OR | $P$-value | Coeff. | OR | $P$-value | Coeff. | OR | $P$-value |
| $\alpha_0$ | -5.7716 | 0.0031 | *** | -4.025 | 0.018 | *** | -4.884 | 0.008 | *** |
| $NT_{t-1}$ | 0.2176 | 1.2430 | *** | 0.588 | 1.800 | *** | 0.373 | 1.452 | *** |
| $Abs\_T\_Imb_{t-1}$ | -0.4805 | 0.6185 | *** | -0.171 | 0.843 | | 0.116 | 1.123 | |
| $R_{t-1}$ | 0.2675 | 1.3066 | *** | 0.060 | 1.062 | | -0.257 | 0.774 | ** |
| $RS_{t-1}$ | 0.0422 | 1.0431 | ** | 0.200 | 1.221 | *** | 0.577 | 1.780 | *** |
| $N$ | 16,312 | | | 4,713 | | | 4,149 | | |
| $N_{y=0}$ | 16,239 | 99.55% | | 4,583 | 97.24% | | 4,102 | 98.87% | |
| $N_{y=1}$ | 73 | 0.45% | | 130 | 2.76% | | 47 | 1.13% | |
| $R^2$ | 0.84% | | | 2.98% | | | 2.01% | | |

This Table reports results of Equation 18. The dependent variable is the occurrence of an EPM at time $t$ and the independent variables include an intercept, the number of trades ($NT$), the absolute trade imbalance ($Abs\_T\_Imb$), the absolute return ($R$), and the relative spread ($RS$). All variables, excepting the intercept, are lagged by one period and are standardized. $N$ is the number of observations, $N_{y=0}$ ($N_{y=1}$) is the number of non-events (events). We also report the R-squared. Panel A, B, and C are respectively subsamples before the bubble (before May, 24 2017), during the bubble (between May, 25 2017 and January, 28 2018), and after the bubble (after January, 28 2018). *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

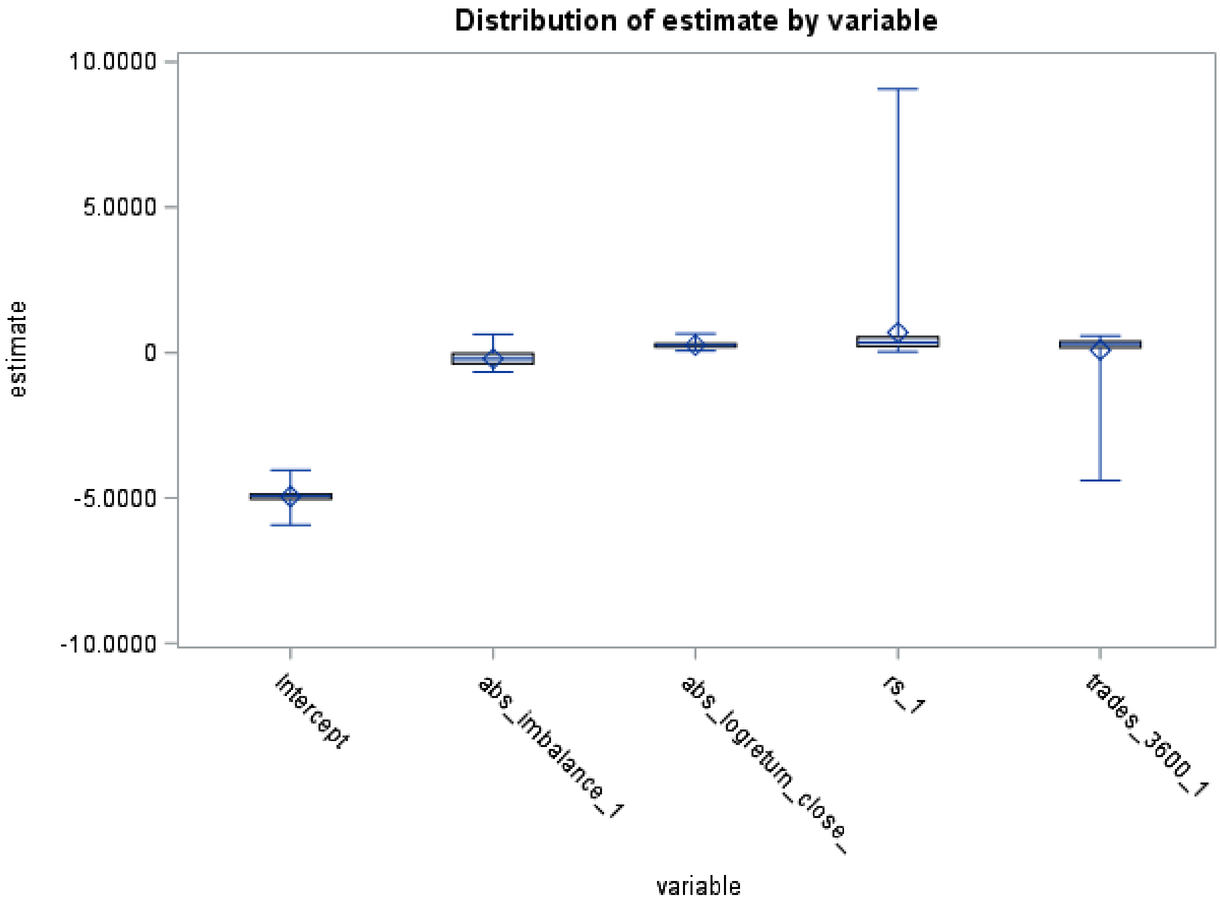
## 5. Robustness tests

In this section, we run 3 robustness checks. First, we opt for a $p$-value counter methodology, i.e. we estimate Equation 18 on each platform/cryptocurrency combination. Second, we estimate a RELOGIT specification, to take the scarcity of event into account. Third, we extend our set of candidate variables and use a general-to-specific approach.

### 5.1. "P-value counter methodology"

We estimate Equation 18 on each "platform/cryptocurrency" combination, leading to 25 estimations. In Figure 7, we summarize the distribution of the obtained coefficients and in Table 6, we report the number of positive / negative coefficients, as well as their significance level.

Figure 7: Boxplot - estimated coefficients




This figure summarizes the distribution of the obtained coefficients from estimating Equation 18 on each combination platform/cryptocurrency. The dependent variable is the occurrence of an EPM at time $t$ and the independent variables include an intercept, the number of trades ($NT$), the absolute trade imbalance ($Abs\_T\_Imb$), the absolute return ($R$), and the relative spread ($RS$). All variables, excepting the intercept, are lagged by one period and are standardized.

Table 6: Pvalue counter

| Variable | $\alpha_0$ | $NT_{t-1}$ | $Abs\_T\_Imb_{t-1}$ | $R_{t-1}$ | $RS_{t-1}$ |
|---|---|---|---|---|---|
| Negative | | | | | |
| 1% | 25 | | 9 | | |
| 5% | | 1 | 3 | | |
| 10% | | | 1 | | |
| N.S. | | 1 | 8 | | |
| Positive | | | | | |
| 1% | | 17 | 2 | 19 | 18 |
| 5% | | 1 | | 2 | 3 |
| 10% | | 2 | 1 | | |
| N.S. | | 3 | 1 | 4 | 4 |

This Table reports the number of positive or negative coefficient that we obtain when we estimate Equation 18 on each combination cryptocurrency / platform. The dependent variable is the occurrence of an EPM at time $t$ and the independent variables include an intercept, the number of trades ($NT$), the absolute trade imbalance ($Abs\_T\_Imb$), the absolute return ($R$), and the relative spread ($RS$). All variables, excepting the intercept, are lagged by one period and are standardized. N.S. stands for 'not significant'.

### 5.2. RELOGIT

EPMs are by definition rare events and the use of a LOGIT regression may induce some biases due to the disequilibrium between the number of events ($EPM_{99/99.9} = 1$) and non-events ($EPM_{99/99.9} = 0$). To take this imbalance into account, we extend our baseline model to a Rare Event LOGIT (RELOGIT). According to Mazza (2019, p. 8), this correction is *'a perfect solution for rare events.'* This method is discussed by King and Zeng (2001a,b) and by Cook et al. (2018) in the field of political science and international conflicts. Mazza (2019) compares several logistic models and indicates that a LOGIT with fixed effects (FELOGIT) and conditional logit (CLOGIT) are the best alternatives when it comes to analyzing rare events, while controlling for fixed effects.

In the case of rare events, coefficients are biased and underestimated. Following Mazza (2019), the bias may be computed as:

$$\begin{aligned}
\hat{\beta} - bias(\hat{\beta}) &= \tilde{\beta} \\
bias(\hat{\beta}) &= (\mathbf{X'WX})^{-\mathbf{1}}\mathbf{X'W}\xi \\
\xi_j &= 0.5Q_{jj}[(1+w_1)\hat{\pi}_j - w_1] \\
\mathbf{Q} &= \mathbf{X}(\mathbf{X'WX})^{-\mathbf{1}}\mathbf{X'} \\
\mathbf{W} &= diag[\hat{\pi}_j(1-\hat{\pi}_j)w_j] \\
w_0 &= \frac{1-\tau}{1-\bar{y}} \\
w_1 &= \frac{\tau}{\bar{y}} \\
w_j &= w_1 Y_j + w_0(1-Y_j)
\end{aligned} \tag{21}$$

We report results in Table 7. Even if we study rare events, we can control the scarcity of these events by setting the return threshold. Therefore, the frequency of rare events in the data almost matches the theoretical proportion of these events, and the correction in the RELOGIT brings little changes with respect to the results of Table 3.

Table 7: RELOGIT

| | Coeff. | OR | $P$-value |
|---|---|---|---|
| $\alpha_0$ | -5.1266 | 0.0059 | *** |
| $NT_{t-1}$ | 0.4249 | 1.5295 | *** |
| $Abs\_T\_Imb_{t-1}$ | -0.5164 | 0.5967 | *** |
| $R_{t-1}$ | 0.1954 | 1.2158 | *** |
| $RS_{t-1}$ | 0.0274 | 1.0278 | |
| $N$ | 25,174 | | |
| $N_{y=0}$ | 24,924 | 99.01% | |
| $N_{y=1}$ | 250 | 0.99% | |
| $R^2$ | 1.59% | | |

This Table reports results of Equation 18 when we apply the RELOGIT correction, as explained in Equation 21. The dependent variable is the occurrence of an EPM at time $t$ and the independent variables include an intercept, the number of trades ($NT$), the absolute trade imbalance ($Abs\_T\_Imb$), the absolute return ($R$), and the relative spread ($RS$). All variables, excepting the intercept, are lagged by one period and are standardized. $N$ is the number of observations, $N_{y=0}$ ($N_{y=1}$) is the number of non-events (events). We also report the R-squared. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

### 5.3. General to specific models

Instead of relying on Brogaard et al. (2018) for the choice of the explanatory variables, we use a broader list of candidate variables and opt for a general-to-specific approach in order to select the remaining variables. We use a threshold of statistical significance at 5%. All variables are standardized and lagged by one period. The final model is presented in Table 8. The list of candidates includes number of trades ($NT$), quantity traded ($QT$), volume traded ($VT$), average trade size ($ATS$), average trade volume ($ATV$), trading imbalance ($T\_Imb$), trading imbalance in quantity ($Q\_Imb$), trading imbalance in volume ($V\_Imb$), absolute trading imbalance ($Abs\_T\_Imb$), absolute trading imbalance in quantity ($Abs\_Q\_Imb$), absolute trading imbalance in volume ($Abs\_V\_Imb$), relative spread ($RS$), quoted spread ($QS$), median relative spread ($Median\_RS$), median quoted spread ($Median\_QS$), depth dollar ($DEPTH$), depth dollar at the 5 best quotes ($DEPTH5$), log-return ($R$), absolute log-return ($Abs\_R$), amihud ($Amihud$), slope ($Slope$), dispersion ($Dispersion$), and VWAP ($VWAP$). Results are presented in Table 8.

Table 8: General to specific

| | Coeff. | OR | $P$-value |
|---|---|---|---|
| $\alpha_0$ | -5.4049 | 0.0045 | *** |
| $NT_{t-1}$ | 1.1656 | 3.2078 | *** |
| $QT_{t-1}$ | 0.2640 | 1.3021 | *** |
| $VT_{t-1}$ | -1.0537 | 0.3486 | *** |
| $ATV_{t-1}$ | 0.5448 | 1.7242 | *** |
| $Abs\_T\_Imb_{t-1}$ | 0.5930 | 1.8095 | *** |
| $QS_{t-1}$ | -0.2882 | 0.7496 | *** |
| $Median\_RS_{t-1}$ | 0.1122 | 1.1187 | *** |
| $R_{t-1}$ | -0.0958 | 0.9087 | *** |
| $Dispersion_{t-1}$ | 0.7925 | 2.2088 | *** |
| $VWAP_{t-1}$ | -0.2821 | 0.7542 | ** |
| $N$ | 25,174 | | |
| $N_{y=0}$ | 24,924 | 99.01% | |
| $N_{y=1}$ | 250 | 0.99% | |
| $R^2$ | 2.28% | | |

This Table reports the results of Equation 18. The dependent variable is the occurrence of an EPM at time $t$ and the list of candidate independent variables includes number of trades ($NT$), quantity traded ($QT$), volume traded ($VT$), average trade size ($ATS$), average trade volume ($ATV$), trading imbalance ($T\_Imb$), trading imbalance in quantity ($Q\_Imb$), trading imbalance in volume ($V\_Imb$), absolute trading imbalance ($Abs\_T\_Imb$), absolute trading imbalance in quantity ($Abs\_Q\_Imb$), absolute trading imbalance in volume ($Abs\_V\_Imb$), relative spread ($RS$), quoted spread ($QS$), median relative spread ($Median\_RS$), median quoted spread ($Median\_QS$), depth dollar ($DEPTH$), depth dollar at the 5 best quotes ($DEPTH5$), log-return ($R$), absolute log-return ($Abs\_R$), amihud ($Amihud$), slope ($Slope$), dispersion ($Dispersion$), and VWAP ($VWAP$). All variables, excepting the intercept, are lagged by one period and are standardized. $N$ is the number of observations, $N_{y=0}$ ($N_{y=1}$) is the number of non-events (events). We also report the R-squared. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

## 6. Conclusion

In this paper, we investigate the liquidity and trading dynamics around EPMs. Based on Brogaard et al. (2018), we identify EPMs as absolute return higher than a given threshold. We find that during EPMs, trading volume strongly increases, while the effect on liquidity is rather mixed as both depth and spreads increase. Next, we analyze whether these variables help explain the occurrence of an EPM. We start by analyzing Bitcoin in the platform Bitfinex. Then, we extend our analysis to a multi-platforms and multi-cryptocurrencies universe. In addition to a traditional LOGIT methodology, we also use a RELOGIT framework. Our results suggest that trading activity, measured by the number of trades and return are useful predictors to explain the occurrence of EPMs. As far as relative spread is concerned, the results are more mixed.

## References


Aalborg, H. A., P. Molnár, and J. E. de Vries (2019). What can explain the price, volatility and trading volume of bitcoin? *Finance Research Letters 29*, 255–265.

Aggarwal, D. (2019). Do bitcoins follow a random walk model? *Research in Economics 73*(1), 15–22.

Al-Yahyaee, K. H., W. Mensi, I. M. W. Al-Jarrah, A. Hamdi, and S. H. Kang (2019). Volatility forecasting, downside risk, and diversification benefits of bitcoin and oil and international commodity markets: A comparative analysis with yellow metal. *The North American Journal of Economics and Finance 49*, 104–120.

Al-Yahyaee, K. H., W. Mensi, and S.-M. Yoon (2018). Efficiency, multifractality, and the long-memory property of the bitcoin market: A comparative analysis with stock, currency, and gold markets. *Finance Research Letters 27*, 228–234.

Ali, R., J. Barrdear, R. Clews, and J. Southgate (2014). The economics of digital currencies. *Quarterly Bulletin Q3*, 276–286.

Aloosh, A. and S. Ouzan (2019). The psychology of cryptocurrency prices. *Finance Research Letters*.

Amihud, Y. (2002). Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets 5*(1), 31–56.

Aysan, A. F., E. Demir, G. Gozgor, and C. K. M. Lau (2019). Effects of the geopolitical risks on bitcoin returns and volatility. *Research in International Business and Finance 47*, 511–518.

Baek, C. and M. Elbeck (2015). Bitcoins as an investment or speculative vehicle? A first look. *Applied Economics Letters 22*(1), 30–34.

Baur, D. G., T. Dimpfl, and K. Kuck (2018). Bitcoin, gold and the us dollar–a replication and extension. *Finance Research Letters 25*, 103–110.

Baur, D. G., K. Hong, and A. D. Lee (2018). Bitcoin: medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money 54*, 177–189.

Blau, B. M. (2017). Price dynamics and speculative trading in bitcoin. *Research in International Business and Finance 41*, 493–499.

Bleher, J. and T. Dimpfl (2019). Today I got a million, tomorrow, I don't know: on the predictability of cryptocurrencies by means of google search volume. *International Review of Financial Analysis 63*, 147–159.

Bouoiyour, J. and R. Selmi (2015a). Bitcoin price: is it really that new round of volatility can be on way? *Munich Personal RePEc Archive*, 1–14.

Bouoiyour, J. and R. Selmi (2015b). What does bitcoin look like? *Annals of Economics & Finance 16*(2).

Bouoiyour, J., R. Selmi, et al. (2016). Bitcoin: a beginning of a new phase. *Economics Bulletin 36*(3), 1430–1440.

Bouri, E., R. Gupta, C. K. M. Lau, D. Roubaud, and S. Wang (2018). Bitcoin and global financial stress: A copula-based approach to dependence and causality in the quantiles. *The Quarterly Review of Economics and Finance 69*, 297–307.

Bouri, E., C. K. M. Lau, B. Lucey, and D. Roubaud (2019). Trading volume and the predictability of return and volatility in the cryptocurrency market. *Finance Research Letters 29*, 340–346.

Bouri, E., S. J. H. Shahzad, and D. Roubaud (2019). Co-explosivity in the cryptocurrency market. *Finance Research Letters 29*, 178–183.

Brandvold, M., P. Molnár, K. Vagstad, and O. C. A. Valstad (2015). Price discovery on bitcoin exchanges. *Journal of International Financial Markets, Institutions and Money 36*, 18–35.

Brauneis, A. and R. Mestel (2018). Price discovery of cryptocurrencies: bitcoin and beyond. *Economics Letters 165*, 58–61.

Briere, M., K. Oosterlinck, and A. Szafarz (2015). Virtual currency, tangible return: portfolio diversification with bitcoin. *Journal of Asset Management 16*(6), 365–373.

Brogaard, J., A. Carrion, T. Moyaert, R. Riordan, A. Shkilko, and K. Sokolov (2018). High frequency trading and extreme price movements. *Journal of Financial Economics 128*(2), 253–265.

Canh, N. P., U. Wongchoti, S. D. Thanh, and N. T. Thong (2019). Systematic risk in cryptocurrency market: Evidence from dcc-mgarch model. *Finance Research Letters 29*, 90–100.

Chaim, P. and M. P. Laurini (2018). Volatility and return jumps in bitcoin. *Economics Letters 173*, 158–163.

Chaim, P. and M. P. Laurini (2019). Is bitcoin a bubble? *Physica A: Statistical Mechanics and its Applications 517*, 222–232.

Chamberlain, G. (1980). Analysis of covariance with qualitative data. *Review of Economic Studies 47*(0), 225–238.

Cheah, E.-T. and J. Fry (2015). Speculative bubbles in bitcoin markets? An empirical investigation into the fundamental value of bitcoin. *Economics Letters 130*, 32–36.

Chen, C. Y.-H. and C. M. Hafner (2019). Sentiment-induced bubbles in the cryptocurrency market. *Journal of Risk and Financial Management 12*(2), 53.

Chevapatrakul, T. and D. V. Mascia (2019). Detecting overreaction in the bitcoin market: A quantile autoregression approach. *Finance Research Letters 30*, 371–377.

Chu, J., S. Nadarajah, and S. Chan (2015). Statistical analysis of the exchange rate of bitcoin. *PloS one 10*(7), e0133678.

Ciaian, P., M. Rajcaniova, et al. (2018). Virtual relationships: short-and long-run evidence from bitcoin and altcoin markets. *Journal of International Financial Markets, Institutions and Money 52*, 173–195.

Cook, S. J., J. C. Hays, and R. J. Franzese (2018). Fixed effects in rare events data: a penalized maximum likelihood solution. *Political Science Research and Methods*, 1–14.

Corbet, S. and P. Katsiampa (2019). Asymmetric mean reversion of bitcoin price returns. *International Review of Financial Analysis*.

Corbet, S., B. Lucey, M. Peat, and S. Vigne (2018). Bitcoin futures —- What use are they? *Economics Letters 172*, 23–27.

Corbet, S., B. Lucey, and L. Yarovaya (2018). Datestamping the bitcoin and ethereum bubbles. *Finance Research Letters 26*, 81–88.

Corbet, S., A. Meegan, C. Larkin, B. Lucey, and L. Yarovaya (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters 165*, 28–34.

Corrado, C. J. (2011). Event studies: A methodology review. *Accounting & Finance 51*(1), 207–234.

Coupé, T. (2005). Bias in conditional and unconditional fixed effects logit estimation: A correction. *Political Analysis 13*(3), 292–295.

da Silva Filho, A. C., N. D. Maganini, and E. F. de Almeida (2018). Multifractal analysis of bitcoin market. *Physica A: Statistical Mechanics and its Applications 512*, 954–967.

de Souza, M. J. S., F. W. Almudhaf, B. M. Henrique, A. B. S. Negredo, D. G. F. Ramos, V. A. Sobreiro, and H. Kimura (2019). Can artificial intelligence enhance the bitcoin bonanza. *The Journal of Finance and Data Science 5*(2), 83–98.

Demir, E., G. Gozgor, C. K. M. Lau, and S. A. Vigne (2018). Does economic policy uncertainty predict the bitcoin returns? An empirical investigation. *Finance Research Letters*.

Donier, J. and J.-P. Bouchaud (2015). Why do markets crash? Bitcoin data offers unprecedented insights. *PloS one 10*(10), e0139356.

Dwyer, G. P. (2015). The economics of bitcoin and similar private digital currencies. *Journal of Financial Stability 17*, 81–91.

Dyhrberg, A. H. (2016a). Bitcoin, gold and the dollar – a GARCH volatility analysis. *Finance Research Letters 16*, 85–92.

Dyhrberg, A. H. (2016b). Hedging capabilities of bitcoin. Is it the virtual gold? *Finance Research Letters 16*, 139–144.

Easley, D., M. O'Hara, and S. Basu (2019). From mining to markets: The evolution of bitcoin transaction fees. *Journal of Financial Economics*.

Eom, C., T. Kaizoji, S. H. Kang, and L. Pichl (2019). Bitcoin and investor sentiment: Statistical characteristics and predictability. *Physica A: Statistical Mechanics and its Applications 514*, 511–521.

Fang, L., E. Bouri, R. Gupta, and D. Roubaud (2019). Does global economic uncertainty matter for the volatility and hedging effectiveness of bitcoin? *International Review of Financial Analysis 61*, 29–36.

Fang, W., S. Tian, and J. Wang (2018). Multiscale fluctuations and complexity synchronization of bitcoin in china and us markets. *Physica A: Statistical Mechanics and its Applications 512*, 109–120.

Firth, D. (1993). Bias reduction of maximum likelihood estimates. *Biometrika 80*(1), 27–38.

Fischer, T. G., C. Krauss, and A. Deinert (2019). Statistical arbitrage in cryptocurrency markets. *Journal of Risk and Financial Management 12*(1), 31.

Gandal, N., J. Hamrick, T. Moore, and T. Oberman (2018). Price manipulation in the bitcoin ecosystem. *Journal of Monetary Economics 95*, 86–96.

Garcia, D., C. J. Tessone, P. Mavrodiev, and N. Perony (2014). The digital traces of bubbles: feedback cycles between socio-economic signals in the bitcoin economy. *Journal of the Royal Society Interface 11*(99), 20140623.

Glaser, F., K. Zimmermann, M. Haferkorn, M. C. Weber, and M. Siering (2014). Bitcoin-asset or currency? Revealing users' hidden intentions.

Greene, W. (2004). The behaviour of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects. *The Econometrics Journal 7*(1), 98–119.

Heinze, G. (2006). A comparative investigation of methods for logistic regression with separated or nearly separated data. *Statistics in medicine 25*(24), 4216–4226.

Heinze, G. and M. Schemper (2002). A solution to the problem of separation in logistic regression. *Statistics in medicine 21*(16), 2409–2419.

Ji, Q., E. Bouri, C. K. M. Lau, and D. Roubaud (2019). Dynamic connectedness and integration in cryptocurrency markets. *International Review of Financial Analysis 63*, 257–272.

Kang, W. and W. Y. Yeo (2008). Liquidity beyond the best quote: a study of the NYSE limit order book.

Katz, E. (2001). Bias in conditional and unconditional fixed effects logit estimation. *Political Analysis*, 379–384.

Khuntia, S. and J. Pattanayak (2018). Adaptive market hypothesis and evolving predictability of bitcoin. *Economics Letters 167*, 26–28.

Kim, T. (2017). On the transaction cost of bitcoin. *Finance Research Letters 23*, 300–305.

King, G. and L. Zeng (2001a). Explaining rare events in international relations. *International Organization 55*(03), 693–715.

King, G. and L. Zeng (2001b). Logistic regression in rare events data. *Political analysis 9*(2), 137–163.

Kjærland, F., A. Khazal, E. Krogstad, F. Nordstrøm, and A. Oust (2018). An analysis of bitcoin's price dynamics. *Journal of Risk and Financial Management 11*(4), 63.

Klein, T., H. P. Thu, and T. Walther (2018). Bitcoin is not the new gold – a comparison of volatility, correlation, and portfolio performance. *International Review of Financial Analysis 59*, 105–116.

Koutmos, D. (2018). Bitcoin returns and transaction activity. *Economics Letters 167*, 81–85.

Kristoufek, L. (2013). Bitcoin meets Google Trends and Wikipedia: quantifying the relationship between phenomena of the internet era. *Scientific reports 3*, 3415.

Lahmiri, S. and S. Bekiros (2018). Chaos, randomness and multi-fractality in bitcoin market. *Chaos, solitons & fractals 106*, 28–34.

Lee, C. M. and M. J. Ready (1991). Inferring trade direction from intraday data. *Journal of Finance 46*(2), 733–746.

Liu, J., I. W. Marsh, P. Mazza, and M. Petitjean (2019). Factor structure in cryptocurrency returns and volatility. *working paper*.

Mazza, P. (2019). Controlling for rare events and fixed effects in a logistic regression framework: A review of the alternatives. *working paper*.

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. In P. Z. (ed.) (Ed.), *Frontiers in Economics*, pp. 105–142. New York: Academic Press.

McLeay, M., A. Radia, and R. Thomas (2014). Money creation in the modern economy. *Bank of England Quarterly Bulletin Q1*.

Nadarajah, S. and J. Chu (2017). On the inefficiency of bitcoin. *Economics Letters 150*, 6–9.

Næs, R. and J. A. Skjeltorp (2006). Order book characteristics and the volume–volatility relation: Empirical evidence from a limit order market. *Journal of Financial Markets 9*(4), 408–432.

Neyman, J., E. L. Scott, et al. (1948). Consistent estimates based on partially consistent observations. *Econometrica 16*(1), 1–32.

Panagiotidis, T., T. Stengos, and O. Vravosinos (2018). On the determinants of bitcoin returns: A LASSO approach. *Finance Research Letters 27*, 235–240.

Phillips, P. C., Y. Wu, and J. Yu (2011). Explosive behavior in the 1990s nasdaq: When did exuberance escalate asset values? *International economic review 52*(1), 201–226.

Phillips, P. C. and J. Yu (2011). Dating the timeline of financial bubbles during the subprime crisis. *Quantitative Economics 2*(3), 455–491.

Pieters, G. and S. Vivanco (2017). Financial regulations and price inconsistencies across bitcoin markets. *Information Economics and Policy 39*, 1–14.

Rogojanu, A. and L. Badea (2014). The issue of competing currencies. Case study-bitcoin. *Theoretical & Applied Economics 21*(1).

Takaishi, T. (2018). Statistical properties and multifractality of bitcoin. *Physica A: statistical mechanics and its applications 506*, 507–519.

Thies, S. and P. Molnár (2018). Bayesian change point analysis of bitcoin returns. *Finance Research Letters 27*, 223–227.

Tiwari, A. K., R. Jana, D. Das, and D. Roubaud (2018). Informational efficiency of bitcoin—an extension. *Economics Letters 163*, 106–109.

Trabelsi, N. (2018). Are there any volatility spill-over effects among cryptocurrencies and widely traded asset classes? *Journal of Risk and Financial Management 11*(4), 66.

Trimborn, S. and W. K. Härdle (2018). Crix an index for cryptocurrencies. *Journal of Empirical Finance 49*, 107–122.

Urquhart, A. (2016). The inefficiency of bitcoin. *Economics Letters 148*, 80–82.

Urquhart, A. (2017). Price clustering in bitcoin. *Economics letters 159*, 145–148.

Urquhart, A. (2018). What causes the attention of bitcoin? *Economics Letters 166*, 40–44.

Vidal-Tomás, D. and A. Ibañez (2018). Semi-strong efficiency of bitcoin. *Finance Research Letters 27*, 259–265.

Vidal-Tomás, D., A. M. Ibáñez, and J. E. Farinós (2019). Herding in the cryptocurrency market: Cssd and csad approaches. *Finance Research Letters 30*, 181–186.