Do Investors Feedback Trade in the Bitcoin—and Why?

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Abstract

We empirically examine whether feedback traders are active in the Bitcoin and the extent to which their presence is affected by a series of noise-related factors (sentiment; volume; liquidity) at three different frequencies (hourly; daily; weekly) for the April 2013–July 2019 period based on Bitstamp data. Our findings suggest that positive feedback trading grows stronger for higher (hourly; daily) frequencies, with its presence manifesting itself mainly during periods of high/improving sentiment and high/rising volume/liquidity. Additional tests reveal that the significance of hourly feedback trading is identified during hours corresponding to the trading hours of major European/North American markets. Overall, our results confirm extant literature evidence on the prevalence of noise trading in cryptocurrencies, while further showcasing that the factors motivating feedback trading in other asset classes (equities; ETFs; futures) exhibit similar effects over the presence of feedback traders in the cryptocurrency market.

Keywords: feedback trading; Bitcoin; sentiment; volume; liquidity

JEL classification: G15; G40; G41

1. Introduction

Feedback trading (i.e., trading on historical prices) constitutes a rather popular strategy among investors internationally (Choi and Skiba, 2015). Its presence has been confirmed at both the micro (for various investor-types, such as retail, institutional and overseas) and macro (using aggregate data) levels, and for various market states (including rising/falling prices and regulatory changes) in a variety of asset classes (equities; bonds; derivatives; exchange-traded funds; property; currencies).[1] Evidence from these asset classes, involving instruments bearing fundamental values, demonstrates that feedback trading can be the strategy of choice of both sophisticated investors (who, though aware of fundamentals, choose to rely on past prices motivated by various rational considerations[2]) and noise traders (whose lack of knowledge of fundamentals justifies their reliance on past prices).

However, the advent of cryptocurrencies during the past decade has given rise to a novel market segment of ever-growing popularity among investors (Chester, 2017)—and one largely viewed as being of little or zero fundamental value (Cheah and Fry, 2015; Yermack, 2015). Although this would suggest the significance of noise trading in cryptocurrencies (e.g., Cheung, Roca, and Su, 2015; Fry and Cheah, 2016), it is interesting to note that very little is known to date (Silva et al., 2019; King and Koutmos, 2021) about the presence and determinants of feedback trading in the cryptocurrency market. This is a rather interesting issue, since, if feedback traders are active in cryptocurrencies, their presence will produce an impact on the market dynamics of this asset class, given the established (Koutmos, 2014) association between feedback trading and several properties of financial time series (such as autocorrelation and volatility). What is

[1] See the review of Koutmos (2014) which surveys some of that evidence.
[2] Fund managers, for instance, have been found to feedback trade more strongly when trading small capitalization stocks (Lakonishok, Shleifer, and Vishny, 1992; Wermers, 1999; Sias, 2004), motivated by the opacity of those stocks' informational environment (due to limited analyst following, little is known about them). Additionally, rational speculators may resort to feedback trading in order to exploit the trading conduct of their noise counterparts (De Long et al., 1990).

more, identifying the key determinants of their presence can offer trading opportunities for other investors, who can, consequently, devise *ad hoc* exploitive strategies.

This paper aims at addressing this issue by investigating feedback trading in the Bitcoin, the world's largest cryptocurrency, for the period from April 15th, 2013 to July 15th, 2019. Drawing on Bitstamp (BTC/USD) tick data, we estimate feedback trading based on three different frequencies (hourly; daily; weekly) to establish whether its presence is a function of investors' trading horizons. We report positive feedback trading for the hourly and daily (but not the weekly) frequencies, with its magnitude growing the strongest for hourly estimations. This suggests that feedback traders in the Bitcoin-market chase rather short-lived trends, possibly due to Bitcoin's high volatility at those frequencies. The significance of positive feedback trading at higher frequencies may also be motivated by its profitability potential, considering recent evidence (Chu, Chan, and Zhang, 2020) on the profitability of high frequency momentum trading in the cryptocurrency market. In addition, the stronger presence of feedback trading at the hourly frequency is coupled with substantial inefficiencies, reflected through significant first-order negative autocorrelation of hourly returns. [3]

We then assess whether feedback trading varies across different states of factors, whose relationship with noise trading has been established in the literature. We initially condition feedback trading on sentiment[4], proxying for the latter via order flow imbalance (OFIB), as proposed by Kumar and Lee (2006), Chelley-Steeley, Lambertides, and Savva (2019). Conditional on whether sentiment is high or low (defined here as whether OFIB in period *t* is

[3] Research on Bitcoin (Takaishi, 2018; Vidal-Tomás, 2020) has often relied on multiple frequencies, in view of the coin's differential time-series properties across frequencies; as these studies suggest, inefficiencies in Bitcoin's series tend to rise in magnitude as one examines higher frequencies. The latter is confirmed in our study, though, of course, it is not possible to ascertain causality (i.e., whether feedback traders cause these inefficiencies or whether inefficiencies motivate their presence, even though both possibilities are theoretically valid). For more on cryptocurrencies' inefficiencies at high frequencies, see Eross et al. (2019), Baur et al. (2019) and Zargar and Kumar (2019).

[4] The role of sentiment in the Bitcoin-market has been explored in Baig, Blau, and Sabah (2019) and Eom et al. (2019), who find that investor sentiment interacts significantly with price-clustering and volatility in the Bitcoin-market.

higher or lower than its previous 30-periods' moving average value[5]), we find that high (low) sentiment periods entail positive feedback trading for all three frequencies (the weekly frequency only). Conditional on improving or deteriorating sentiment (i.e., on whether OFIB in period t is larger or smaller than its previous period's value), we find that improving sentiment breeds positive feedback trading for the hourly and daily frequencies, with deteriorating sentiment presenting us with a more mixed picture (negative feedback trading for the hourly and positive feedback trading for the weekly frequency). The more pronounced presence of positive feedback trading during high/improving sentiment periods is in line with evidence from earlier studies on positive sentiment boosting trend-chasing in futures (Kurov, 2008) and exchange-traded funds (Chau, Deesomsak, and Lau, 2011). In addition, we further notice that feedback traders in the Bitcoin tend to be on the buy- (sell-) side at higher (lower) frequencies for high/improving (low/deteriorating) sentiment states. This suggests that feedback traders purchase Bitcoins motivated by short (and quite possibly, transient) positive shifts in sentiment, with their selling being more associated with relatively longer and negative sentiment shifts.

Our next step is to explore whether feedback trading varies with Bitcoin's trading activity. Toward this end, we employ two proxies, namely trading volume and liquidity. When we condition feedback trading on Bitcoin's volume, results suggest that positive feedback trading is overwhelmingly significant during periods of high volume (defined here as those periods when volume is above its previous 30-periods' moving average) for the hourly and daily frequencies (again growing the strongest for the hourly estimations). Conditioning feedback trading on Bitcoin's period-on-period volume changes, we find that positive feedback trading is significant during periods of rising volume (all three frequencies), while also being present during decreasing volume periods for the daily frequency only. When feedback trading is

[5] *i.e*. the moving average value of the previous 30-hours/-days/-weeks, depending on the frequency examined.

conditioned on Bitcoin's / (proxied via the Amihud (2002) measure), the estimates obtained denote a rather mixed picture, with positive feedback trading manifesting itself for high (low) liquidity periods for the hourly (daily) frequency. When feedback trading is conditioned on period-on-period liquidity changes, we find that positive feedback trading is significant only for periods when liquidity has increased over the previous period (for the hourly and daily frequencies). Taken together, with results from estimations conditioning feedback trading on volume, our findings suggest that positive feedback trading in the Bitcoin is associated with rising/high values of both liquidity and, especially, volume. These results are in line with established literature evidencing noise traders in general (Black, 1986) and feedback traders in particular (Kodres, 1994; Miwa and Ueda, 2011) boosting volume in capital markets. What is more, our results may also reflect the fact that high volume enhances the feasibility of feedback trading (indeed, any trading strategy), as it allows those pursuing feedback trading patterns to do so with minimal frictions.

Considering our evidence that feedback trading is more pronounced at the hourly frequency, we further examine whether its presence at this frequency can be identified with specific trading hours of international markets, as this would allow us some preliminary insight into its approximate locus of significance during the day. To that end, we condition feedback trading on hourly-intervals falling within and outside the trading hours of European and North American exchanges (08:00–21:00 UTC). We consequently find significant positive feedback trading between 08:00–21:00 UTC hours only. Although this implies that Bitcoin's feedback traders likely originate from the European and North American markets, one should bear in mind that cryptocurrencies trade around the clock and, as such, it is equally plausible that part of their activity during the 08:00–21:00 UTC window is due to night-trading from Asian markets.

Our findings produce original contributions to the behavioural finance literature, by showcasing that feedback trading in the Bitcoin grows stronger at higher frequencies, thus denoting that cryptocurrency traders chase trends within rather short horizons. This is perhaps unsurprising, considering that advances in financial technology (algorithmic and online trading), allowing for the tracking of trends at such frequencies, are enjoying increasing popularity among even relatively less sophisticated investors (cryptocurrencies' main clientele, as evidenced by Corbet, McHugh, and Meegan, 2017; Yelowitz and Wilson, 2015; many of whom are active day-traders internationally as shown by Barber et al., 2014).

Second, by showing that positive feedback trading grows stronger as frequencies become higher, we also denote the possibility of it being a key determinant of cryptocurrencies' excess volatility, a phenomenon widely reported in earlier studies using daily data[6] (considering the established link of positive feedback trading to volatility[7]). Third, to the extent that positive feedback trading in the Bitcoin appears more pronounced in the presence of positive sentiment and rising/high trading activity, this suggests that it is likely noise-driven (in view of noise traders' traditional interaction with both sentiment and volume; Black, 1986; Kodres, 1994; Miwa and Ueda, 2011). Such results help confirm extant evidence (Cheung, Roca, and Su, 2015; Fry and Cheah, 2016) on the prevalence of noise traders in cryptocurrency markets.

Our paper bears interesting implications for the investment community; to the extent that Bitcoin's market is typified by inefficiencies (affirmed by the significant autocorrelations

[6] The presence of high volatility in daily Bitcoin-returns has been established by a large array of studies, including Katsiampa (2017), Phillip, Chan, and Peiris (2018), Chaim and Laurini (2018), Troster et al. (2019) and Katsiampa, Corbet, and Lucey (2019). Evidence from these studies suggests that Bitcoin-volatility exceeds several times that of equity markets, with cross-cryptocurrency studies (Baur and Dimpfl, 2018; Katsiampa, Corbet, and Lucey, 2019) broadly confirming this for other cryptocurrencies as well. Although cryptocurrencies' volatility is high, it tends to grow stronger following positive shocks, contrary to extant evidence (e.g. Bollerslev, Engle, and Nelson, 1994) from financial time series on the volatility leverage effect (which is reflected via higher volatility following negative shocks).

[7] Research has established the presence of positive feedback trading during periods with negative return autocorrelation and high volatility (see e.g., Sentana and Wadhwani ,1992).

documented in this paper)[8] and positive feedback traders at higher frequencies, this implies the potential for exploiting (inefficiencies and feedback traders) via *ad hoc* strategies at those frequencies, e.g. by conditioning one's trades on anticipated shifts of sentiment or volume. Additionally, the presence of positive feedback traders in the Bitcoin suggests the (potentially profitable) exploitation of trading by rational speculators (e.g. via front-running prior to the announcement of cryptocurrency-related news, *à la* De Long et al., 1990). From a regulatory perspective, our findings raise the possibility of positive feedback traders potentially acting as a destabilizing force for the wider cryptocurrency segment. This would be something particularly detrimental from a social welfare viewpoint, considering the wide popularity of cryptocurrencies among retail investors. It is important, therefore that regulatory authorities issue regular communications to the wider public, outlining the risks of investing in cryptocurrencies, and cautioning against their treatment as lottery-type investments. As regards researchers, our findings indicate the need for expanding the pool of studied behavioural influences in cryptocurrency trading by researching additional behavioural factors whose effect has been established in the literature, such as e.g. anchoring and the disposition effect (considering that both involve reference points—and, hence, past prices—in decision-making, something rather relevant to the feedback trading studied here).

The rest of this paper is structured as follows: Section 2 presents an overview of the theoretical foundations and empirical evidence relevant to feedback trading; as well as discussing the key properties of cryptocurrencies as an asset class along with summarizing extant evidence on the behaviour of its investors. Section 3 presents the data, alongside descriptive statistics as well as our empirical design. Section 4 discusses the results, while Section 5 offers concluding remarks and outlines the implications of our research.

[8] These results are relevant to extant research (Takaishi, 2018; Vidal-Tomás, 2020), where Bitcoin is found to generate amplified inefficiencies for intraday frequencies.

2. Theoretical background

2.1 Feedback trading

According to the weak form of the Efficient Market Hypothesis (Fama, 1991), prices reflect all information contained in historical trading data, thus precluding the possibility of trading profitably on past prices. Feedback trading runs counter to this. As a concept, it encompasses any investment strategy relying on historical data (normally prices) aiming at extrapolating past trends in anticipation of their recurrence, with concomitant profitable exploitation. The breadth of this view encompasses various strategies, both rational (such as portfolio insurance), as well as behavioral (such as technical analysis), under the umbrella of feedback trading (Koutmos, 2014). By and large, these strategies aim at either trailing trends or bucking them. The former case leads to positive feedback trading (buying when prices rise; selling when they decline), with the latter leading to negative feedback trading (selling when prices go up and buying when they fall). Since feedback trading relies on the identification of trends, its widespread pursuit can result in increased serial correlation of returns (Cutler, Poterba, and Summers, 1990) and exacerbate their volatility (Farmer, 2002; Farmer and Joshi, 2002). Consequently, this can enhance return-predictability, force prices to depart from fundamentals, and increase inefficiencies in markets (Koutmos, 2014).

Although feedback trading runs counter to market efficiency, it is often practiced for rather rational reasons related to observational learning. With prices constituting a noisy statistical summary of market activity, investors can rely on them to infer information about the trades of their peers without the need to monitor them *per se* (Hirshleifer and Teoh, 2003) and this can foster feedback trading due to two distinct reasons. The first is rational speculation (De Long et al., 1990); whereby speculators take advantage of their informational superiority by trading ahead of forthcoming news, whose arrival-time they are privy to. In this case, their early trading helps create price-trends, which noise traders ride on, and which rational speculators can observe and profitably exploit. The second cause of feedback trading relates to feedback trading constituting a response to risk, and so manifesting in a variety of ways. For example, investors trading stocks of small capitalization are faced with high information risk (given the limited analyst-following of those stocks) and may consider extrapolating from past prices as a means of tackling informational uncertainty (Lakonishok, Shleifer, and Vishny, 1992; Sias, 2004; Voronkova and Bohl ,2005; Wermers, 1999). Also, investors trading in overseas markets may view themselves as being at an informational disadvantage versus their indigenous peers and, may, hence choose to feedback trade as a means of inferring information (Brennan and Cao, 1997; Choe, Kho, and Stulz, 1999; Dahlquist and Robertsson, 2001; Froot, O'connell, and Seasholes, 2001; Kalev, Nguyen, and Oh; 2008; Kang, 1997; Kim and Wei, 2002a; Kim and Wei, 2002b; Lin and Swanson, 2008). In addition, portfolio insurance and stop-loss orders, which are employed to reduce the risk (and amount) of losses during price-slumps, can also amplify (downward) trends in markets (Kodres, 1994; Osler, 2005). Furthermore, feedback trading may also be practiced for reputational reasons. This is the case with fund managers practicing window-dressing (selling their portfolio's losers and buying outperforming stocks, in effect positive feedback trading) in order to generate a positive image of their skills (Grinblatt, Titman, and Wermers, 1995). From a less-than-perfectly rational perspective, feedback trading can be motivated via the extensive use of investment styles, in particular momentum (positive feedback) and contrarian (negative feedback) trading strategies (Galariotis, 2014); as well as technical analysis, which traditionally relies on historical price-patterns (Fong and Yong, 2005). A series of behavioral biases (anchoring; conservatism; disposition-effect; overconfidence) and heuristics (representativeness) can also prompt investors to extrapolate from historical prices (Barberis, Shleifer, and Vishny, 1998; Barberis and Thaler, 2003; Brown et al., 2006).

Empirical evidence strongly suggests the popularity of (particularly, positive) feedback trading among institutional investors worldwide (Choi and Skiba, 2015). Significant momentum trading has been documented for fund managers in the US (Choi and Sias, 2009; Celiker, Chowdhury, and Sonaer, 2015; Froot and Teo, 2008; Frijns, Gilbert, and Zwinkels, 2013; Sias, 2004), South Korea (Choe, Kho, and Stulz, 1999) and Taiwan (Hung, Lu, and Lee, 2010). UK funds have been found to exhibit strong contrarian tendencies (Wylie, 2005), while fund managers in Germany have been reported to both positive (Walter and Moritz Weber, 2006) and negative (Kremer and Nautz, 2013) feedback trade. Retail investors have also been found to engage in strong (bidirectional) feedback trading in a variety of markets, including Australia (Colwell, Henker, and Walter, 2008), Finland (Grinblatt and Keloharju, 2000), Germany (Dorn, Huberman, and Sengmueller, 2008) and the US (Barber et al., 2009). At the aggregate (macro) market level, there exists ample evidence suggesting the presence of (predominantly) positive feedback trading in equity indices (Chau and Deesomsak, 2015; Koutmos, 1997; Koutmos and Saidi, 2001; Schuppli and Bohl, 2010; Sentana and Wadhwani, 1992; Watanabe, 2002), index futures (Kurov, 2008)[9], fixed-income (Cohen and Shin, 2003), currencies (Aguirre and Saidi, 1999; Danielsson and Love, 2006; Laopodis, 2005), housing prices (Clapp and Tirtiroglu, 1994), agricultural futures (Gregory, Rochelle, and Rochelle, 2013; Wu et al., 2015) and exchange-traded funds (Chau, Deesomsak, and Lau, 2011; Charteris et al., 2014). Evidence from the macro level shows that positive feedback trading is associated with negative first-order return autocorrelation and is directionally asymmetric, appearing stronger during down-markets.

2.2 Cryptocurrencies

[9] However, note the limited evidence of positive feedback trading reported in Antoniou, Koutmos, and Pericli (2005) for index futures and Chau, Holmes, and Paudyal (2008) for single-stock futures.

Cryptocurrencies are peer-to-peer digital assets which are not subject to regulatory oversight by traditional monetary authorities and, as such, are of a decentralized nature.[10] The advent of this new asset class can be traced to the aftermath of the 2007–2009 global financial crisis that prompted a reduction in public trust towards governments and central banking systems (Weber, 2016). This period saw the launch of the Bitcoin, in effect the world's first cryptocurrency, in 2009. Its inventor bore the assumed name of Satoshi Nakamoto and, overall, justified Bitcoin's introduction as a response to the weaknesses and the high dispute-mediation costs of existing electronic payment systems (Blau, 2017). At its core, Bitcoin allows transacting parties to deal directly with each other without mediation. Transactions are verified and encrypted via mathematical cryptography proofs, with the coin's unique encryption protocol helping identify each Bitcoin-unit directly; thereby providing protection from fraud to both parties (Blau, 2017). Bitcoin soon gained wide media attention, thus prompting the launch of various other cryptocurrencies and leading to the establishment of a completely new asset class. Although Bitcoin and the first cryptocurrencies launched in its aftermath functioned as experimental commodities traded among computer programming enthusiasts (Brandvold et al., 2015), the surge in public interest (particularly from retail speculators as noted by Corbet, McHugh, and Meegan, 2017) culminated into a booming new market segment with a massive number of initial coin offerings (ICOs) observed over the recent years.[11] As of February 2020, there were around 5,100 cryptocurrencies trading with a market capitalization hovering just over $282 billion.[12] Despite the growing popularity of some of these (e.g. Ethereum, Litecoin etc), Bitcoin has remained the largest cryptocurrency in capitalization-terms, accounting for over 60% (February 2020) of the market value of this asset class. [13]

[10] Of course excluding here the near-future unveiling of a centralized cryptocurrency by the People's Bank of China.
[11] 2018 alone witnessed 1253 ICOs (source: https://www.icodata.io/stats/2018), with 2017 entailing a further 343.
[12] Source: https://coinmarketcap.com/.
[13] Source: https://coinmarketcap.com/.

A key issue here pertains to establishing fundamental valuations in this asset class. Several studies (Cheah and Fry, 2015; Yermack, 2015) posit that cryptocurrencies' fundamental values are zero. Others studies suggest cryptocurrency valuations are ambivalent at best. [14] Such opaque fundamentals are expected to be particularly inviting to noise traders, whose presence in this market segment has, indeed, been confirmed (Cheung, Roca, and Su, 2015; Fry and Cheah, 2016). The latter is further supported by the fact that cryptocurrencies' clientele comprises mainly of retail investors (Corbet, McHugh, and Meegan, 2017; Yelowitz and Wilson, 2015), who constitute the prime candidates for noise trading (Barber et al., 2009). In view of this, it should come as no surprise that cryptocurrencies' return-dynamics are affected by investor sentiment (Cheah and Fry, 2015; Kristoufek, 2015), exhibit excess volatility and heavy tails (Gkillas and Katsiampa, 2018; Katsiampa, 2017; Phillip, Chan, and Peiris, 2018), and are prone to speculative bubbles (Cheah and Fry, 2015; Dowd, 2014).

Research on the trading patterns of cryptocurrency investors has demonstrated that they herd to various degrees (Bouri, Gupta, and Roubaud, 2019; Kaiser and Stöckl, 2020; Kallinterakis and Wang, 2019; Vidal-Tomás, Ibáñez, and Farinós, 2019;), with their herding being affected by a variety of factors (such as size, volatility and volume). In addition, recent research (King and Koutmos, 2021; Silva et al., 2019) shows that cryptocurrencies accommodate (positive and negative) feedback trading. Such research, however, does not extend to investigating possible determinants.[15]

3. Data and Methodology

3.1 Data

[14] See, for example, Fantazzini et al. (2016).

[15] Some studies (Anghel, 2021; Hitam et al., 2019; Torres et al., 2020) have demonstrated how machine-learning techniques can be utilized to exploit information hidden in cryptocurrencies' time series of prices; machine-learning techniques have traditionally been used in technical analysis (Nazário et al., 2017) and, as such, could be viewed as capable of contributing to feedback trading in this asset class.

Transaction data (including time-stamped prices and trading volume) for BTC/USD (Bitstamp)[16] are collected from https://api.bitcoincharts.com/v1/csv/ for the period spanning from April 15, 2013 to July 15, 2019. We record a total of 32,863,285 transactions, which we employ to construct hourly, daily and weekly time series of returns and volume over the sample period. Transactions recorded at the same second are considered as one single transaction for which we aggregate the volume and calculate the volume-weighted price.

We now turn to delineating how sentiment and liquidity are calculated. With regards to sentiment, we follow Kumar and Lee (2006), and Chelley-Steeley, Lambertides, and Savva (2019) by using the order flow imbalance (OFIB) as a sentiment-proxy. For each sampling frequency, the OFIB of period *t* is given by:

$$OFIB_t = \frac{\sum_{i=1}^{N_t}(VB_{it} - VS_{it})}{\sum_{i=1}^{N_t}(VB_{it} + VS_{it})} \tag{1}$$

where N_t is the number of transactions at time *t* over each sampling frequency and VB_{it} (VS_{it}) is the dollar-denominated buy (sell) volume for period *t*. Given that our data do not flag the direction of the transaction and do not contain historical bid-ask quotes, we rely on the tick rule to assign trade direction. Namely, a trade is classified as buyer- (seller-) initiated if the transaction price is above (below) the last different transaction price.[17]

As regards the Amihud (2002) measure, it is calculated as follows for period *t* (in line with Amihud, 2002):

$$AMH_t = \frac{1{,}000{,}000 * |R_t|}{P_t * V_t} \tag{2}$$

[16] We opted for BTC/USD values from Bitstamp, considering the fact that it is the largest cryptocurrency exchange internationally (Zargar and Kumar, 2019) and its wide popularity among relevant research in this asset class (see e.g. Brandvold et al., 2015; Baur et al., 2019; Choi, 2020).

[17] According to traditional market microstructure literature (e.g., O'Hara, 1995), order-flows reflect innovations in information signals dispersed across market participants. By construction, OFIB varies with the heterogeneity in investors' beliefs, contingent on whether these beliefs are dominated by bullish (buy-side volume prevails) or bearish (sell-side volume prevails) sentiments. Its usage here as a control variable hinges on the fact that we wish to gauge whether feedback trading varies contingent on whether it is optimistic or pessimistic sentiment that prevails in the market each period.

where P_t reflects the closing price of period t, V_t the volume of period t and R_t the (log-differenced) return corresponding to period t. By construction, the higher (lower) the value of the Amihud measure, the lower (higher) liquidity becomes.

Table 1 provides descriptive statistics for Bitcoin's log-differenced returns (Panel A), OFIB (Panel B), volume (Panel C) and the Amihud measure (Panel D). Bitcoin's mean return is positive for all frequencies, growing in magnitude as the frequency grows lower. The magnitude of the Jacque-Bera test-statistics denotes that all return-series exhibit substantial departures from normality, something further attested by the skewness and kurtosis measures and the magnitude of the test-statistics of the Ljung–Box portmanteau test on the first and second moments of returns. The mean values of OFIB are negative, suggesting that average sentiment over the sample period across all frequencies was pessimistic. This is likely due to the large fall in Bitcoin's prices following December 2017 that lasted for about a year and led to a substantial loss (over 80%) of its value. Volume exhibits rising mean values as one moves towards lower frequencies (something unsurprising), while the Amihud measure drops in value as we move from the hourly to the weekly frequency, suggesting that liquidity rises, on average, as the trading horizon grows (in line with the volume-statistics reported in Panel C).

3.2 Methodology

To empirically assess feedback trading in the Bitcoin market, we utilize the Sentana and Wadhwani (1992) model. This model assumes an interaction between rational speculators and feedback traders. The demand function for rational speculators is:

$$S_t = [E_{t-1}(R_t) - \alpha_0]/\theta\sigma_t^2 \tag{3}$$

where S_t is the fraction of the Bitcoin-market corresponding to rational speculators at time t, R_t is the observed (log-differenced) return in period t, $E_{t-1}(R_t)$ is the expectation of the (log-differenced) return in period t as of the immediately previous period (*t-1*), α_0 is the risk-free interest rate, σ_t^2 is the conditional variance of period t and θ is the coefficient of risk aversion. Assuming $\theta > 0$, the term $\theta\sigma_t^2$ is the required risk premium.

Feedback traders' demand function is:

$$F_t = \gamma R_{t-1} \tag{4}$$

where γ is the feedback trading parameter; positive (negative) values of γ suggest the presence of positive (negative) feedback traders.

Given that all shares are held at equilibrium (i.e., $S_t + F_t = 1$), we have:

$$E_{t-1}(R_t) - \alpha_0 = \theta\sigma_t^2 - \gamma\theta\sigma_t^2 R_{t-1} \tag{5}$$

We estimate Equation (5) by assuming R_t's rational expectation ($R_t = E_{t-1}(R_t) + \varepsilon_t$), where ε_t is an *i.i.d.* error term:

$$R_t = \alpha_0 + \theta\sigma_t^2 - \gamma\theta\sigma_t^2 R_{t-1} + \varepsilon_t \tag{6}$$

The term $-\gamma\theta\sigma_t^2 R_{t-1}$ implies that when volatility is high, the demand for shares by feedback traders will be high, resulting in stronger return-autocorrelation. This becomes positive (negative) in the presence of negative (positive) feedback trading. To control for the possibility that autocorrelation may result from other sources (such as nonsynchronous trading), we employ the following specification:

$$R_t = \alpha_0 + \theta\sigma_t^2 + (\phi_0 + \phi_1\sigma_t^2)R_{t-1} + \varepsilon_t \tag{7}$$

where ϕ_0 captures the effects of non-synchronous trading; given $\phi_1 = -\gamma\,\theta$, positive (negative) feedback trading is reflected via a significantly negative (positive) value for ϕ_1.

In view of cryptocurrencies' relatively less sophisticated, retail clientele, and evidence from previous studies on this group's behavioural trading patterns (see the discussion in Section 2.2), we propose our first hypothesis (which we test for using Equation (7)):

Hypothesis 1. Bitcoin accommodates significant feedback trading.

With regards to the effects of sentiment, volume and liquidity over feedback trading, we propose the following hypotheses:

Hypothesis 2. Feedback trading appears stronger during periods of high sentiment.

Hypothesis 3. Feedback trading appears stronger during periods of improving sentiment.

Hypothesis 4. Feedback trading appears stronger during periods with high volume.

Hypothesis 5. Feedback trading appears stronger during periods with rising volume.

Hypothesis 6. Feedback trading appears stronger during periods with high liquidity.

Hypothesis 7. Feedback trading appears stronger during periods with rising liquidity.

Hypotheses 2 and 3 are motivated via literature evidence on optimistic sentiment boosting positive feedback trading in futures (Kurov, 2008), and in exchange-traded funds (Chau, Deesomsak, and Lau, 2011), and in line with earlier evidence from international equity markets (Grinblatt and Keloharju, 2001; Lamont and Thaler, 2003). Furthermore, to the extent that optimistic periods' positive mood can reduce investors' perception of riskiness in decision making and prompt them to resort to heuristics in their processing (Schwarz, 1990; Forgas, 1998), this can render feedback trading a viable choice, given the importance of extrapolating from historical price trends as a heuristic (Kallinterakis et al., 2020). In addition, external habit formation (individuals benchmarking their utility versus that of their peers; Abel, 1990) can also foment positive feedback trading during positive sentiment periods; by watching many of their peers enjoy profits during such periods, investors may well opt for trading in the (upward) trend's direction of those periods in search for profits in order to ensure that their utility does not suffer. What is more, investors realizing profits from trading on optimistic sentiment's up-trend, will grow more confident in their skills and be encouraged to trade more aggressively by betting on the continuation of respective trends (Barber et al., 2007). Consequently, this enhances the potential for trend-chasing.

Hypotheses 4 to 7 are motivated by noise trading, in general (Black, 1986), and feedback trading, in particular (Kodres, 1994; Miwa and Ueda, 2011) tending to be associated with rising trading activity in the market. What is more, higher liquidity renders it easier for traders to see their orders timely executed; thus facilitating the pursuit of feedback trading (indeed, any trading strategy), as has been argued by Andrikopoulos et al. (2020).

We test empirically for Hypotheses 2–7 on the premises of the following specification:

$$R_t = \beta_0 D + \beta_1(1-D) + \theta_0 D\sigma_t^2 + \theta_1(1-D)\sigma_t^2 + D\left(\phi_{0,0} + \phi_{1,0}\sigma_t^2\right)R_{t-1} + (1-D)\left(\phi_{0,1} + \phi_{1,1}\sigma_t^2\right)R_{t-1} + \varepsilon_t \tag{8}$$

Here D is a dummy variable, which is designated as follows for each of our hypotheses:

Hypothesis 2: Here we condition feedback trading on periods of high-versus-low sentiment. We define high- (low-) sentiment periods as those for which OFIB is greater (smaller) than its previous 30-periods' moving average value. In these cases, we set D = 1 for low sentiment periods, and zero otherwise.

Hypothesis 3: Here feedback trading is conditioned on periods of improving-versus-deteriorating sentiment. Improving (deteriorating) sentiment periods are defined as those for which OFIB is greater (smaller) than the respective previous period's value. In these cases, we set D = 1 for deteriorating sentiment periods, and zero otherwise.

Hypothesis 4: We condition feedback trading on periods of high-versus-low volume, defining high- (low-) volume periods as those for which volume is greater (smaller) than the respective previous 30-periods' moving average value. In these cases, we set D = 1 for low volume periods, and zero otherwise.

Hypothesis 5: Feedback trading is conditioned on periods of rising-versus-declining volume. Rising (declining) volume periods are defined as those for which volume is greater (smaller) than the respective previous period's value. In these cases, we set D = 1 for declining volume periods, and zero otherwise.

Hypothesis 6: In this hypothesis, we condition feedback trading on periods of high-versus-low liquidity. We define high- (low-) liquidity periods as those for which the Amihud measure is smaller (greater) than its previous 30-periods' moving average value. In these cases, we set D = 1 for high liquidity periods, and zero otherwise.

Hypothesis 7: Here, feedback trading is conditioned on periods of rising-versus-declining liquidity. Rising (declining) liquidity periods are defined as those for which the Amihud measure is smaller (greater) than its previous period's value. In these cases, we set D = 1 for increasing liquidity periods, and zero otherwise.

Estimating Equations (7) and (8) requires identifying a specification for the conditional variance (σ_t^2). To that end, we select the asymmetric GARCH specification proposed by Glosten et al. (1993), as it controls for the established leverage effect in volatility (Bollerslev, Engle, and Nelson, 1994):

$$\sigma_t^2 = \omega + \kappa\sigma_{t-1}^2 + \lambda\varepsilon_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2 \tag{9}$$

Here I_{t-1} is a dummy variable, equalling one, if the lagged shock is negative, and zero otherwise. Significantly positive values of δ indicate that volatility is asymmetric, appearing stronger following negative, as opposed to positive, shocks.

4. Results-discussion

4.1 Are feedback traders active in the Bitcoin market?

Table 2 reports the maximum likelihood estimates for unconditional feedback trading (Equations (7) and (9)) for all three frequencies. Our conditional variance estimates show that volatility is highly persistent in all cases (κ is always significantly[18] positive, declining monotonically as one moves from the hourly to the weekly frequency) and responds significantly to news (λ is always significantly positive, increasing monotonically as one moves from the hourly to the weekly frequency), yet not strongly asymmetrically[19] (δ is significantly positive only at the hourly frequency). With respect to feedback trading, results from all tests reveal the presence of positive feedback trading ($\varphi_1 < 0$), whose significance is observed for hourly and daily frequencies, of which the hourly is stronger. These results are in line with King and Koutmos (2021) and Silva et al. (2019), who also report the presence of positive feedback traders in the Bitcoin and confirm earlier findings (Cheung, Roca, and Su, 2015; Fry and Cheah, 2016) on the presence of noise traders in cryptocurrency markets—not particularly surprising considering the evidence of strong retail clientele in that asset class (Corbet, McHugh, and Meegan, 2017; Yelowitz and Wilson, 2015). This suggests that feedback traders in the Bitcoin-market chase rather short-lived trends, possibly due to Bitcoin's high volatility at those frequencies prompting them to focus on narrower investment horizons. Chasing trends at higher frequencies indicates the potential for more pronounced inefficiencies for those frequencies[20], something reflected through the significantly negative φ_0-coefficient (indicative of negative first-order return-autocorrelation) of the hourly frequency only. What is more, the significance of positive feedback trading at higher frequencies may also be due to its profitability-potential, given recent evidence (Chu, Chan, and Zhang, 2020) demonstrating that

[18] For brevity purposes, statistical significance is defined here at the 10 percent level of significance.
[19] In line with Baur and Dimpfl (2018), who find that cryptocurrencies tend to accommodate reverse-asymmetric volatility effects (their volatility grows stronger following positive shocks) or insignificant asymmetric volatility altogether.
[20] Examples of such inefficiencies at high frequencies are the intraday patterns documented (Eross et al., 2019; Baur et al., 2019; Zargar and Kumar, 2019) for several cryptocurrencies; the presence of those patterns can both be motivated as well as exploited by feedback traders.

momentum strategies at high frequencies generate significantly positive returns in the cryptocurrency market. Overall, the above results confirm the presence of feedback traders in the Bitcoin market, thus leading us to accept Hypothesis 1.

4.2 Does sentiment impact feedback trading?

Table 3 presents the estimates from Equations (8) and (9) conditioning feedback trading on high/low (Panel A) and improving/deteriorating (Panel B) sentiment. Panel A reveals the presence of consistently significant positive feedback trading during high sentiment periods for all three frequencies, most strongly so for the hourly one (for which $\phi_{1,1}$ assumes its largest absolute value). Low sentiment periods entail - at the weekly frequency only - significant positive feedback trading, whose magnitude appears larger than that of high sentiment periods at that frequency ($|\phi_{1,0}| > |\phi_{1,1}|$). The picture for improving/deteriorating sentiment periods is more mixed; whereas improving sentiment periods accommodate significant positive feedback trading (hourly and daily frequencies), the presence of negative (positive) feedback trading is also evident during deteriorating sentiment periods for the hourly (weekly) frequency. On the face of those results, positive feedback trading tends to grow more pronounced during high/improving sentiment periods (particularly for higher – hourly; daily – frequencies), in line with evidence from earlier studies on positive sentiment boosting trend-chasing in futures (Kurov, 2008) and exchange-traded fund (Chau, Deesomsak, and Lau, 2011) markets. Since returns are expected to be, on average, positive during positive sentiment periods, this suggests that feedback traders in the Bitcoin are more likely to appear on the buy-side for higher (hourly; daily) frequencies; this is further confirmed via the significant negative feedback trading at the hourly frequency during deteriorating sentiment periods (i.e. when returns would, on average, be expected to be negative).[21] On the other hand, the positive feedback trading documented

[21] By definition, negative feedback traders buy when prices fall and sell when they rise.

during low/deteriorating sentiment periods for the weekly frequency indicates that feedback traders are likely to be on the sell-side[22] at lower frequencies. As a result, feedback traders tend to be on the buy- (sell-) side at higher (lower) frequencies for high/improving (low/deteriorating) sentiment states. This suggests that feedback traders are motivated to purchase Bitcoins by short (and quite possibly, transient) positive shifts in sentiment. On the other hand, their selling is more associated with relatively longer and negative-sentiment shifts.[23]

4.3 Does trading activity impact feedback trading?

Table 4 presents the estimates from Equations (8) and (9) when feedback trading is conditioned on high/low (Panel A) and rising/falling (Panel B) volume. We notice that volume exerts a much more discernible impact over feedback trading, with positive feedback trading being almost[24] exclusively concentrated within high (hourly and daily frequencies) and rising (all frequencies) volume periods. The estimates obtained when conditioning feedback trading on liquidity are presented in Table 5, both for high/low liquidity (Panel A) and rising/falling liquidity (Panel B) states. Unlike sentiment and volume, liquidity appears to interact less with feedback trading; positive feedback trading is documented for high liquidity (hourly frequency), low liquidity (daily frequency) and rising liquidity (hourly and daily frequency). Overall, these results suggest that positive feedback trading is motivated by enhanced trading activity, manifesting itself mainly during periods of high/rising volume and liquidity and almost exclusively for the hourly and daily frequencies. These findings confirm established

[22] By definition, positive feedback traders sell when prices fall and buy when they rise and returns during low/deteriorating sentiment periods are expected to be, on average, negative.
[23] Our results support earlier evidence (Baur and Dimpfl, 2018) on noise trading in cryptocurrencies being stronger during positive return periods; showing that volatility grows, on average, stronger among cryptocurrencies following positive shocks, the authors attribute this to noise investors buying aggressively into cryptocurrencies when the latter exhibit price-rallies.
[24] Weakly significant (10% level) positive feedback trading is also observed for declining volume periods at the daily frequency.

(Black, 1986) evidence on the association between noise trading and volume, and are in line with earlier research (Kodres, 1994; Miwa and Ueda, 2011) on the link between feedback trading and volume. It is further possible that these results reflect the fact that volume reduces frictions in the trading process and allows for quicker order-execution, thus facilitating the pursuit of feedback trading strategies (Andrikopoulos et al., 2020).[25]

4.4 Additional tests

The results presented in Tables 2–5 illustrate that positive feedback trading surfaces mainly for the two higher frequencies (hourly and daily). In this section, we focus on the hourly frequency and investigate whether the significance of feedback trading at this level exhibits any particular concentration, contingent on the trading times of major international markets. To that end, we re-estimate feedback trading at the hourly frequency using Equation (8), conditional upon whether the hours fall within the trading times of Western (Europe; North America) markets or Asia-Pacific ones. We set $D = 1$ for the hours of the 08:00 – 21:00 UTC interval (when European and North American markets are open), and zero otherwise (for times when Asia-Pacific markets are open).[26] Examining the results in Table 6, we see that positive feedback traders are active during the 08:00 – 21:00 UTC interval only. To the extent that hourly positive feedback trading in our previous results is found to be present for high/rising volume/liquidity periods without exception, our findings are comparable to Eross et al. (2019), who show that Bitcoin's intraday volume and liquidity are the highest when major global exchanges are open. Although this would suggest that positive feedback traders' activity coincides with that of major Western markets, ascertaining that they originate from these markets is impossible, both due to lack of relevant (e.g. transaction) data and also due to the fact that part of this activity

[25] We have repeated our estimations using 15-, 45- and 60-period moving averages for high versus low sentiment/ volume / liquidity. Our results are qualitatively and quantitatively similar to the results with 30-period moving average values and support our original findings. We thank an anonymous referee for making this suggestion.

[26] By "open" here we refer to each major market's trading activity; not all markets in Europe/North America (Asia-Pacific) will be simultaneously open within (outside) the 08:00 – 21:00 UTC interval.

might hail from non-Western markets (e.g. from feedback traders in the Asia-Pacific active overnight when their region's markets are closed).[27]

We further performed two additional tests to assess the robustness of our findings. First, in view of Bitcoin's meteoric rise culminating in its first historical peak (USD 19,497.40) on December 16th, 2017 and its slump thereafter which initiated a period of rather pronounced volatility we re-estimated Equation (7) before and after December 16th, 2017 for all three frequencies. Results suggest the presence of significant positive feedback trading across all three frequencies pre-December 16th, 2017, with its intensity being a straight function of the frequency (the higher the frequency, the stronger the positive feedback trading); the years following December 16th, 2017 witness negative (positive) feedback trading at the hourly (daily) frequency, with the weekly frequency entailing no evidence of feedback trading. These results suggest that feedback traders are robustly present in the Bitcoin market, particularly at higher (hourly; daily) frequencies and confirm the findings reported earlier in this paper. Second, we re-estimated Equation (7) using BTC/USD data from the Gemini cryptocurrency exchange, in order to gauge whether the findings reported here are Bitstamp-specific; the estimates obtained suggest the presence of significant positive feedback trading for the hourly and daily frequencies. Results are not presented here for brevity purposes and are available from the authors on request.

5. Concluding remarks

Investors in the cryptocurrency market tend to be less sophisticated and prone to pursuing behavioral trading patterns. In this paper, we explore whether feedback traders are active in the

[27] Eross et al. (2019) state in p. 75 that the volume patterns documented in their paper suggest that "[…] European and North American investors are the main drivers of the volume traded of USD denominated Bitcoin", yet also state in the same page (footnote 10) that "Although investors can trade outside the usual trading hours of stock markets, consistent with the literature we assume that they will conduct most of their trading during normal stock market trading hours". We repeat here that, in the absence of transaction data and the possible presence of overnight trading, it is impossible to be assertive as per the geographical origin of feedback trading.

Bitcoin market and whether a series of noise-related factors (sentiment; volume; liquidity) impact their presence across various frequencies (hourly; daily; weekly). Drawing on Bitstamp data for 2013–2019, we show that positive feedback trading is particularly strong for the hourly/daily frequency, more so when sentiment is high/improving and when volume and liquidity are high/rising, in line with extant research on the link between positive sentiment and high volume/liquidity and noise trading patterns. The magnitude of positive feedback trading is strongest for the hourly estimations, being particularly significant at that frequency during major Western exchanges' trading hours. Our findings suggest that feedback traders in the Bitcoin-market chase rather short-lived trends, possibly due to Bitcoin's high volatility at those frequencies, as well as due to the profitability-potential of momentum strategies at high frequencies in the cryptocurrency market.

The evidence presented in this study is of key relevance to the investment community, particularly those investors with a focus in the cryptocurrency market. To the extent that Bitcoin's market is typified by inefficiencies (given the significant autocorrelations documented in this paper) and positive feedback traders at higher frequencies, there is potential for exploiting both (inefficiencies and feedback traders) via *ad hoc* strategies at those frequencies. A trader, for example, could try to exploit Bitcoin's price-trends by bucking the observed sentiment, entering positions during low sentiment periods (when feedback traders, as our results indicate, are likely to be on the sell-side, with prices expected to be low) and unloading them during high sentiment periods (when feedback traders are strongly present on the buy-side, and prices are expected to be high). Another possibility would be for a trader to use a predictive model for the control variables used in this study (sentiment; volume; liquidity) and condition a response to Bitcoin's price-trends on the anticipated shifts of those variables. In addition, the presence of positive feedback traders in the Bitcoin suggests the potential for profitable exploitation of them by rational speculators (e.g. via front-running them prior to the announcement of cryptocurrency-related news, *à la* De Long et al., 1990). This could even possibly be facilitated by using Bitcoin futures/options contracts (Söylemez, 2019) to hedge their positions.

As regards researchers, our findings indicate the need for expanding the pool of studied behavioral influences in cryptocurrency trading by researching additional behavioral factors whose effects have been established in equities and other asset classes. Examples here could include anchoring and the disposition effect, considering that both involve reference points in decision-making (with these reference points often based on past prices, in line with feedback trading).

From a regulatory perspective, the presence of positive feedback traders entails the potential for destabilization in the wider cryptocurrency segment, given the wide popularity of cryptocurrencies among retail investors and the concomitant adverse effects on social welfare. Our results suggest it is important that regulatory authorities issue regular communications to the wider public, outlining the risks of investing in cryptocurrencies and cautioning against their treatment as lottery-type investments.

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Table 1: Descriptive statistics for our sample-variables

	Hourly frequency	Daily frequency	Weekly frequency
Panel A: Bitcoin returns			
Mean	0.0086	0.2162	1.3225
Standard deviation	1.0014	4.4252	12.5442
Maximum	29.8880	33.7486	64.4154
Minimum	-30.6625	-28.0650	-47.9192
Skewness	-0.7380	-0.0761	0.2294
Kurtosis	64.4768	10.5825	6.47945
Jarque-Bera	$8.6109\ 10^{6}$	5459.3354	170.3861
LB (12)	411.1518	36.2613	12.1036
LB^2 (12)	15870.1079	583.5323	154.3284
Panel B: Order Flow Imbalance (OFIB)			
Mean	-0.0187	-0.0283	-0.0292
Standard deviation	0.3583	0.1399	0.0736
Maximum	1.0000	0.5058	0.2295
Minimum	-0.9972	-0.5128	-0.3811
Skewness	0.0192	-0.0407	-0.3440
Kurtosis	2.7304	3.5796	4.5131
Jarque-Bera	168.8251	32.5158	38.2198
LB (12)	1196.5338	167.3972	82.8869
Panel C: Volume			
Mean	500.6992	12003.7965	82634.8050
Standard deviation	741.3779	10969.2956	57137.7270
Maximum	20551.2510	137070.1783	376075.9357
Minimum	0.2725	719.1598	6760.1746
Skewness	6.2886	3.6312	2.0561
Kurtosis	79.5486	26.5377	9.0744
Jarque-Bera	$13.7032\ 10^{6}$	57617.1572	746.5942
LB (12)	92411.1904	3910.7474	424.6171
Panel D: Liquidity (Amihud measure)			
Mean	0.0460	0.0049	0.0021
Standard deviation	0.2404	0.0098	0.0042
Maximum	36.0416	0.2144	0.0347
Minimum	0.0000	0.0000	0.0000
Skewness	74.9382	7.8015	4.9316
Kurtosis	9782.9291	115.3763	32.0493
Jarque-Bera	$2.1785\ 10^{11}$	$1.2223\ 10^{6}$	13058.4200
LB (12)	11649.0920	6446.2831	670.0027

The table contains the following descriptive statistics for the log-differenced returns, order flow imbalance, volume and liquidity (Amihud measure) of Bitcoin for the 15/04/2013 – 15/07/2019 period: mean; standard deviation; maximum value; minimum value; skewness; kurtosis; Jarque-Bera normality test-statistic; Ljung-Box test statistics for twelve lags (first moment); and Ljung-Box test statistics for twelve lags (second moment; Bitcoin-returns only).

Table 2: Maximum likelihood estimates for unconditional feedback trading

	Hourly	Daily	Weekly
α_0	0.0062***	0.0630	0.1710
	(3.7608)	(1.0097)	(0.3682)
θ	0.0296***	0.0153**	0.0061
	(7.3745)	(2.5507)	(1.2644)
ϕ_0	-0.1138***	-0.0016	0.0829
	(-23.336)	(-0.1712)	(1.0180)
ϕ_1	-0.0024***	-0.0016***	-0.0003
	(-2.6594)	(-2.9323)	(-1.3124)
ω	0.0031***	0.2850	17.1232
	(9.1946)	(1.5488)	(1.2362)
κ	0.9018***	0.8330***	0.5717***
	(189.64)	(24.6277)	(3.5420)
λ	0.0782***	0.1726***	0.4534***
	(22.0129)	(8.2268)	(2.6521)
δ	0.0201***	-0.0312	-0.1391
	(3.3256)	(-1.1203)	(-0.7440)

The table presents the maximum likelihood estimates from the following set of equations for the 15/04/2013 – 15/07/2019 period for Bitcoin's log-differenced returns:

$$R_t = \alpha_0 + \theta\sigma_t^2 + (\phi_0 + \phi_1\sigma_t^2)R_{t-1} + \varepsilon_t$$
$$\sigma_t^2 = \omega + \kappa\sigma_{t-1}^2 + \lambda\varepsilon_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$$

Parentheses include the t-statistics of the estimates generated by using White's robust standard errors.
***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table 3: Maximum likelihood estimates for feedback trading conditional on sentiment

	Hourly	Daily	Weekly
Panel A: high versus low sentiment			
β_0	-0.0868***	-0.5077***	-2.9843***
	(-21.4530)	(-5.2985)	(-2.7909)
β_1	0.1109***	0.4740***	1.3060
	(12.9669)	(7.4724)	(1.2917)
θ_0	-0.1274***	-0.0437***	-0.0103
	(-21.0567)	(-4.9326)	(-0.9258)
θ_1	0.1290***	0.0951***	0.0420**
	(2.9668)	(9.6104)	(2.3318)
$\phi_{0,0}$	-0.1333***	-0.0635*	0.0753
	(-6.1387)	(-1.6881)	(0.8231)
$\phi_{1,0}$	0.0090	0.0003	-0.0012**
	(0.3319)	(0.2607)	(-2.2161)
$\phi_{0,1}$	-0.1249***	0.0173	0.1264
	(-11.3328)	(0.2326)	(1.4408)
$\phi_{1,1}$	-0.0069***	-0.0042***	-0.0006*
	(-2.8038)	(-2.7111)	(-1.6915)
ω	0.0027***	0.2148*	6.7705
	(7.5224)	(1.8428)	(1.5730)
κ	0.9239***	0.8644***	0.7299***
	(138.2851)	(29.4134)	(8.3484)
λ	0.0724***	0.1421***	0.3351**
	(4.4321)	(5.7645)	(2.0503)
δ	-0.0126	-0.0329	-0.1500
	(-0.3304)	(-1.4114)	(-1.4411)
Panel B: improving versus deteriorating sentiment			
β_0	-0.0896***	-0.3054***	-1.5480
	(-31.7178)	(-3.6526)	(-1.3888)
β_1	0.1058***	0.4763***	2.6342**
	(20.5572)	(5.7799)	(2.2672)
θ_0	-0.1063***	-0.0507***	-0.0027
	(-10.2342)	(-5.8388)	(-0.2632)
θ_1	0.1778***	0.1216***	0.0378***
	(9.6262)	(10.3457)	(2.6681)
$\phi_{0,0}$	-0.1348***	-0.0784**	0.0913
	(-21.6168)	(-2.1176)	(0.9527)
$\phi_{1,0}$	0.0020***	-0.0002	-0.0009**
	(4.1171)	(-0.1521)	(-2.4984)
$\phi_{0,1}$	-0.1232***	0.0012	0.1958
	(-19.5002)	(0.0318)	(0.7132)
$\phi_{1,1}$	-0.0104***	-0.0031***	-0.0007
	(-3.9464)	(-3.1066)	(-0.8139)
ω	0.0025***	0.2046	13.9837
	(5.7109)	(1.2358)	(0.6030)
κ	0.9285***	0.8718***	0.5936
	(122.4824)	(21.8452)	(1.5151)
λ	0.0713***	0.1406***	0.4431
	(22.0878)	(6.5610)	(1.0580)
δ	-0.0196*	-0.0448	-0.0934
	(-1.8990)	(-1.5277)	(-0.4501)

The table presents the maximum likelihood estimates from the following set of equations for the 15/04/2013 – 15/07/2019 period for Bitcoin's log-differenced returns:

$$R_t = \beta_0 D + \beta_1(1-D) + \theta_0 D\sigma_t^2 + \theta_1(1-D)\sigma_t^2 + D(\phi_{0,0} + \phi_{1,0}\sigma_t^2)R_{t-1} + (1-D)(\phi_{0,1} + \phi_{1,1}\sigma_t^2)R_{t-1} + \varepsilon_t$$

$$\sigma_t^2 = \omega + \kappa\sigma_{t-1}^2 + \lambda\varepsilon_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$$

D is a dummy variable assuming the value of unity during low sentiment (Panel A) and deteriorating sentiment (Panel B) periods. Parentheses include the t-statistics of the estimates generated by using White's robust standard errors.
***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table 4: Maximum likelihood estimates for feedback trading conditional on volume of trade

	Hourly	Daily	Weekly
Panel A: high versus low volume			
β_0	0.0071**	-0.0273	-0.4262
	(2.5002)	(-0.0527)	(-0.3580)
β_1	0.0017	0.3783	2.1499
	(0.7015)	(0.7346)	(1.5317)
θ_0	0.0361***	0.0213*	0.0100
	(6.2905)	(1.7487)	(0.7592)
θ_1	0.0245***	0.0045	-0.0008
	(2.6056)	(0.0482)	(-0.1326)
$\phi_{0,0}$	-0.2033***	-0.1340***	0.0005
	(-34.7227)	(-4.5538)	(0.0098)
$\phi_{1,0}$	0.0037	0.0009	-0.0003
	(0.7961)	(0.5582)	(-0.7386)
$\phi_{0,1}$	0.0134**	0.1744**	0.2207
	(2.3077)	(2.3455)	(1.3387)
$\phi_{1,1}$	-0.0059***	-0.0041***	-0.0003
	(-4.3456)	(-3.4629)	(-1.3554)
ω	0.0032***	0.2834	15.6857
	(9.7529)	(0.4914)	(1.4666)
κ	0.9006***	0.8311***	0.5718***
	(202.4225)	(6.4801)	(4.7244)
λ	0.0778***	0.1732	0.5016***
	(22.5250)	(1.5040)	(2.6001)
δ	0.0232***	-0.0287	-0.2343
	(5.9123)	(-0.3282)	(-1.1172)
Panel B: increasing versus decreasing volume			
β_0	0.0128***	-0.0391	-0.1896
	(6.4987)	(-0.2773)	(-0.1353)
β_1	-0.0033	0.2676**	0.4755
	(-0.8449)	(2.3519)	(0.4100)
θ_0	0.0361***	0.0259***	0.0114
	(4.8027)	(3.1316)	(1.2687)
θ_1	0.0140***	-0.0128	0.0075
	(2.9655)	(-0.8912)	(0.6816)
$\phi_{0,0}$	-0.1703***	-0.1089***	-0.1269
	(-36.9551)	(-3.3971)	(-1.5238)
$\phi_{1,0}$	-0.0004	-0.0014*	0.0001
	(-0.3626)	(-1.8942)	(0.4562)
$\phi_{0,1}$	0.0349***	0.3352***	0.5391***
	(3.9736)	(4.8676)	(3.9771)
$\phi_{1,1}$	-0.0071***	-0.0044***	-0.0011**
	(-5.1700)	(-3.8760)	(-2.4841)
ω	0.0031***	0.2573	14.1623
	(10.1041)	(1.3203)	(1.4908)
κ	0.9020***	0.8409***	0.5821***
	(213.2649)	(22.1241)	(4.6087)
λ	0.0771***	0.1640***	0.5059***
	(25.0725)	(7.1838)	(2.7470)
δ	0.0219***	-0.0297	-0.1959
	(6.8108)	(-0.8840)	(-0.9502)

The table presents the maximum likelihood estimates from the following set of equations for the 15/04/2013 – 15/07/2019 period for Bitcoin's log-differenced returns:

$$R_t = \beta_0 D + \beta_1(1-D) + \theta_0 D\sigma_t^2 + \theta_1(1-D)\sigma_t^2 + D(\phi_{0,0} + \phi_{1,0}\sigma_t^2)R_{t-1} + (1-D)(\phi_{0,1} + \phi_{1,1}\sigma_t^2)R_{t-1} + \varepsilon_t$$

$$\sigma_t^2 = \omega + \kappa\sigma_{t-1}^2 + \lambda\varepsilon_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$$

D is a dummy variable assuming the value of unity during low volume (Panel A) and declining volume (Panel B) periods. Parentheses include the t-statistics of the estimates generated by using White's robust standard errors. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table 5: Maximum likelihood estimates for feedback trading conditional on liquidity

	Hourly	Daily	Weekly
Panel A: high versus low liquidity			
β_0	0.0053**	0.0573	0.6624
	(2.3908)	(1.3666)	(0.8321)
β_1	0.0015	0.3034	2.3779
	(0.4538)	(1.5266)	(0.9557)
θ_0	0.0120**	0.0056	0.0026
	(2.5346)	(1.3109)	(0.3776)
θ_1	0.0678***	0.0293*	-0.0198
	(7.7079)	(1.8016)	(-0.6982)
$\phi_{0,0}$	-0.0258***	-0.0047	0.0760
	(-5.1812)	(-0.3537)	(0.7415)
$\phi_{1,0}$	-0.0019*	0.0000	-0.0002
	(-1.8045)	(-0.0337)	(-0.5387)
$\phi_{0,1}$	-0.5268***	-0.1626	0.8042
	(-52.2742)	(-1.4276)	(1.3422)
$\phi_{1,1}$	-0.0007	-0.0031***	-0.0065
	(-0.5393)	(-3.6832)	(-1.1899)
ω	0.0031***	0.2584	4.1596
	(9.2385)	(1.1646)	(1.0523)
κ	0.9095***	0.8636***	0.8000***
	(206.6368)	(19.5640)	(7.4544)
λ	0.0727***	0.1592***	0.2282
	(18.9929)	(6.2179)	(1.3713)
δ	0.0156***	-0.0657***	-0.0763
	(3.5575)	(-2.9328)	(-0.6870)
Panel B: increasing versus decreasing liquidity			
β_0	0.0029	0.0303	-0.2585
	(1.1588)	(0.8174)	(-0.0801)
β_1	0.0059	0.1229	1.0169
	(1.3914)	(1.0174)	(0.5674)
θ_0	0.0144***	0.0093**	0.0074
	(5.2804)	(2.1276)	(0.4909)
θ_1	0.0419***	0.0255	0.0036
	(5.8717)	(1.6075)	(0.2480)
$\phi_{0,0}$	-0.0319***	-0.0013	0.0906
	(-5.8688)	(-0.1012)	(1.2180)
$\phi_{1,0}$	-0.0038***	-0.0011*	-0.0001
	(-3.3200)	(-1.8105)	(-0.7343)
$\phi_{0,1}$	-0.5340***	-0.2223	-0.0469
	(-46.0474)	(-0.7042)	(-0.0582)
$\phi_{1,1}$	-0.0029	-0.0009	-0.0007
	(-1.5032)	(-0.3314)	(-0.6549)
ω	0.0031***	0.2952	14.1667
	(9.0196)	(1.2914)	(1.1223)
κ	0.9117***	0.8381***	0.6400***
	(205.4520)	(19.9934)	(4.0699)
λ	0.0699***	0.1738***	0.4393**
	(21.9912)	(7.0221)	(2.0305)
δ	0.0167***	-0.0438*	-0.1792
	(5.0307)	(-1.6818)	(-0.9454)

The table presents the maximum likelihood estimates from the following set of equations for the 15/04/2013 – 15/07/2019 period for Bitcoin's log-differenced returns:

$$R_t = \beta_0 D + \beta_1(1-D) + \theta_0 D\sigma_t^2 + \theta_1(1-D)\sigma_t^2 + D(\phi_{0,0} + \phi_{1,0}\sigma_t^2)R_{t-1} + (1-D)(\phi_{0,1} + \phi_{1,1}\sigma_t^2)R_{t-1} + \varepsilon_t$$

$$\sigma_t^2 = \omega + \kappa\sigma_{t-1}^2 + \lambda\varepsilon_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$$

D is a dummy variable assuming the value of unity during periods of low values of the Amihud measure (i.e. high liquidity; Panel A) and declining values of the Amihud measure (i.e. increasing liquidity; Panel B). Parentheses include the t-statistics of the estimates generated by using White's robust standard errors. ***, ** and * denote significance at 1%, 5% and 10%, respectively.

Table 6: Maximum likelihood estimates for hourly feedback trading conditional on major international exchanges' trading times

β_0	0.0112*** (5.5208)
β_1	-0.0008 (-0.1533)
θ_0	0.0290*** (4.5507)
θ_1	0.0312*** (3.3340)
$\phi_{0,0}$	-0.1139*** (-19.4901)
$\phi_{1,0}$	-0.0031** (-2.5635)
$\phi_{0,1}$	-0.1170*** (-13.5067)
$\phi_{1,1}$	0.0014 (0.3265)
ω	0.0031*** (8.6565)
κ	0.9018*** (181.9922)
λ	0.0782*** (20.7382)
δ	0.0199*** (3.1863)

The table presents the maximum likelihood estimates from the following set of equations for the 15/04/2013 – 15/07/2019 period for Bitcoin's log-differenced returns:

$$R_t = \beta_0 D + \beta_1(1-D) + \theta_0 D\sigma_t^2 + \theta_1(1-D)\sigma_t^2 + D(\phi_{0,0} + \phi_{1,0}\sigma_t^2)R_{t-1} + (1-D)(\phi_{0,1} + \phi_{1,1}\sigma_t^2)R_{t-1} + \varepsilon_t$$

$$\sigma_t^2 = \omega + \kappa\sigma_{t-1}^2 + \lambda\varepsilon_{t-1}^2 + \delta I_{t-1}\varepsilon_{t-1}^2$$

D is a dummy variable assuming the value of unity if the hours fall within the 08:00 – 21:00 UTC interval during a day, zero otherwise. Parentheses include the t-statistics of the estimates generated by using White's robust standard errors. ***, ** and * denote significance at 1%, 5% and 10%, respectively.