Annals of Operations Research (2024) 332:579–616
https://doi.org/10.1007/s10479-023-05575-0

ORIGINAL RESEARCH

The great crypto crash in September 2018: why did the cryptocurrency market collapse?

Viktor Manahov[1]

Received: 22 February 2022 / Accepted: 16 August 2023 / Published online: 12 September 2023

Abstract
The cryptocurrency crash on the 5th of September, 2018, resulted in price decreases in 95 of the 100 leading digital currencies. We obtained millisecond data of some of the more prominent cryptocurrencies–bitcoin, ethereum, ripple, bitcoin cash and eos–and some of the smaller cryptocurrencies–neo, nem, omg, tezos and lisk–that were most affected in the crash and investigated what caused the digital market to collapse. We find that the behaviour of the more prominent cryptocurrencies and bitcoin, in particular, was the dominant factor behind the crash. We also find that smaller cryptocurrencies followed the behaviour of the larger ones in the crash. Furthermore, our empirical findings show that the trading behaviour of cryptocurrency traders (CTs) did not trigger the digital market crash. We propose the introduction of a single-cryptocurrency circuit breaker most prominent largest cryptocurrency–bitcoin–that will halt trading during market disruptions.

Keywords Cryptocurrency · Herding behaviour · Market efficiency

1 Introduction

Cryptocurrencies have often been compared to the biggest 'bubbles' in history, such as the Dutch Tulip mania of the seventeenth century, the Mississippi bubble of the eighteenth century, the UK Canal and Railway mania of the nineteenth century, and the more recent Dot-com bubble in 2000. The first crash of the biggest cryptocurrency, bitcoin, occurred in June 2011, when \$8.75 million in bitcoin was stolen from the Mt. Gox[1] exchange through an online attack using stolen passwords; this resulted in the bitcoin price crashing from \$17.51 to \$0.01 on the exchange. The second bitcoin crash was triggered by an incident in which trading at Mt. Gox was suspended between the 11th of April 2013 and the 12th of April

[1] Mt. Gox was a bitcoin exchange based in Japan. The trading venue was launched in July 2010; by 2013 and into 2014 it was handling over 70% of all bitcoin transactions worldwide, as the largest bitcoin intermediary and the world's leading bitcoin exchange. In February 2014, Mt. Gox suspended trading, closed its website and exchange service, and filed for bankruptcy protection from creditors. A year later, the company began liquidation proceedings. Mt. Gox announced that approximately 850,000 bitcoins belonging to customers and the company were missing and likely stolen, an amount valued at more than \$450 million at the time.

✉ Viktor Manahov
viktor.manahov@york.ac.uk

[1] School for Business and Society, University of York, York YO10 5DD, UK

2013 for a 'market cool-down', facilitating a sharp sell-off. As a result, the value of a single bitcoin fell to a low of \$55.59 after the resumption of trading. Mt. Gox's decision to suspend all bitcoin withdrawals on the 7th of February 2014 and to shut down its trading activities on the 25th of February 2014 led to the third crash (Cheung, Roca and Su, 2015). The next bitcoin bubble occurred between December 2017 and December 2018, when the price of the largest cryptocurrency decreased by more than 83%, following a massive increase in value-from \$1,000 at the beginning of 2017 to \$20,000 in December of the same year. The price of the second-largest cryptocurrency by market capitalisation, ethereum, decreased significantly, registering a monthly loss of 56% in August 2015 and 45% in September 2015, following the launch of the cryptocurrency live release, ethereum frontier, in late July 2015 (DiGeorgia, 2018).

On the 5th of September 2018, the value of 95 of the top 100 cryptocurrencies decreased over 24 h, creating a massive sell-off period known as the Great Crypto Crash. During this cryptocurrency meltdown, the value of bitcoin fell by more than 12% to approximately \$6,450. Ethereum experienced an even more significant decrease of 19%, while ripple was down more than 12% and bitcoin cash, eos, neo, and omg decreased by more than 20% (Meyer, 2018). At the same time, the MVIS CryptoCompare Digital Assets 10 Index experienced a decrease of 80% from January 2018 to September 2018. This crash surpassed even Nasdaq Composite Index decline of 78% after the dot-com bubble in 2000.

There are several likely reasons behind the Great Crypto Crash. First, Goldman Sachs abandoned its plans to launch a dedicated cryptocurrency trading desk. The investment bank has been a significant institution related to cryptocurrency trading, having financed the 'bitcoin start-up circle' in 2015 and has expressed interest in launching a crypto trading desk (Meyer, 2018). Second, on the day of the crash, a 'whale'[2] with no previously recorded transactions transferred more than 22,100 bitcoins out of the wallet, leading the market to collapse in price because the support was insufficient to handle this move (CoinSwitch, 2018a, 2018b, 2018c, 2018d, 2018e, 2018f). Third, more than 111,000 bitcoins (worth more than \$700 million) were transferred to the wallets of different trading venues to sell them on the black-market platform Silk Road (Schroeder, 2018).

Therefore, the cryptocurrency market participants would ask the central question: What caused the crash? Also, an important question concerns how cryptocurrency traders (CTs) behave during significant and temporary selling pressure in digital markets. Finance theory suggests that a period of substantial and temporary selling pressure can generate a market collapse even when a fundamental shock is not present (Kirilenko, Kyle, Samadi, and Tuzun, 2017).

To the best of our knowledge, this study represents the first investigation of the crash. We obtained millisecond data of the five largest and five smaller most affected cryptocurrencies in the crash. We investigate what caused these cryptocurrencies to decline during a single

[2] Whales represent people or a group of people working together to hold a large fraction of any particular cryptocurrency; such people can use this to their advantage to manipulate the price of that coin. Whales often deploy a strategy known as 'rinse and repeat', which is very profitable to a whale if executed at the right time. The whale usually begins selling lower than the market rate, which in turn causes cryptocurrency market participants to start selling off their digital money in panic. Then, the whale will re-purchase when the price of the coin reaches a new low level. This process is repeated to accumulate more wealth, more coins, and more control over that particular coin. Another strategy that whales use to manipulate cryptocurrency prices is by deploying buy and sell walls. If the cryptocurrency price decreases, investors will usually purchase at a lower price and sell when it reaches a higher price. A whale can impose either buy or sell walls and closely monitor the price when it hits exactly the anticipated price. Subsequently, the wall vanishes because a whale has cancelled their large buy or sell order.

trading day. More specifically, we examine the implications of bitcoin activities on the rest of the market to shed light on what triggered the cryptocurrency crash.

Our contributions are threefold. First, we observe that the entire cryptocurrency market experienced herding behaviour when prices of the larger cryptocurrencies decreased on the 5th of September 2018.

We also observe that bitcoin could facilitate the herding phenomenon on its own, and the other cryptocurrencies followed the behaviour of bitcoin. Moreover, we find that the more prominent cryptocurrencies–such as bitcoin, ethereum, ripple, bitcoin cash, and eos–drove the remainder of the market during the crash. Therefore, we conclude that the behaviour of the more significant digital currencies-and bitcoin in particular-was the driving factor behind the collapse of digital markets.

Second, we deploy several state-space models to investigate whether the activity of cryptocurrency traders (CTs) caused the crash. Our empirical findings show that the trading behaviour of CTs did not trigger the cryptocurrency crash. Furthermore, we find that significantly more information is incorporated into the bid prices of the ten cryptocurrencies under investigation. An examination of the risk-bearing ability of intermediaries during the market collapse reveals that changes in inventories of CTs are statistically significantly related to contemporaneous and lagged changes in cryptocurrency prices. The regression results indicate that this relationship did not change when cryptocurrency prices significantly decreased during the crash. We also examine market quality before, during, and after the crash, including bid-ask spreads and quote depth measures. We find that bid-ask spreads increased, whereas quote depth decreased after the crash. Overall, the deterioration in market quality can be linked directly to the crash, as it could have had the potential to negatively affect investor confidence, cryptocurrency market participation, and liquidity.

Third, we propose the introduction of single-currency circuit breakers or limit up-limit down trading halts (price limit rule). A single-cryptocurrency circuit breaker for the most major currency–bitcoin–will halt trading during market disruptions like the cryptocurrency crash. Similar to equity markets, we suggest that a trading halt can be triggered after a change of 5% on either side of the average reference price is estimated using the average price over the previous five minutes of trading. Therefore, trading can be halted for five minutes when a bitcoin price decline of more than 5% below the average price of the cryptocurrency over the immediately preceding five-minute trading interval occurs.[3] This should also be the case for a corresponding price increase.

MacDonnell (2014) was among the first to investigate the 2013 bitcoin price crash. This study uses weekly data covering the period from July 2010 until August 2013 and employs Autoregressive Moving Average (ARMA) methodologies and the Log Periodic Power Law (LPPL) models to predict crashes. It can be noted that the LPPL model successfully predicted the crash that took place in December 2013. Similarly, Cheah and Fry (2015) obtained daily closing prices for the Bitcoin Coindesk Index from July 2010 to July 2014 to detect the existence of bubbles. The empirical results reveal that a bubble exists in the bitcoin market and therefore rejects the concept of cryptocurrency market efficiency. Like Cheah and Fry (2015), Donier and Bouchaud's (2015) study reveals that when the bitcoin price is clearly out of bounds-as it was in the pre-April 2013 period-the market is undoubtedly in a bubble state. The authors also show that the three liquidity measures under examination are highly correlated and do indeed predict the amplitude of a cryptocurrency market crash triggered by

[3] Gronwald (2019) used bitcoin daily data from Mt.Gox and Bitstamp and deployed a number of linear and nonlinear GARCH models to observe that bitcoin price dynamics are strongly influenced by extreme price.movements.

a significant sell order imbalance.[4] Bouri, Jalkh, Mornár, and Roubaud (2017) obtained daily bitcoin and commodity indices data from July 2010 to December 2015, and they demonstrate that bitcoin hedge and safe-haven properties against commodities and energy commodities are only present in the pre-crash period, while the corresponding post-crash period acts as a diversifier.

Several studies have investigated the bitcoin price crash of 2017. Yaya, Ogbonna, and Olubusoye (2019) collected daily data on thirteen cryptocurrencies between August 2015 and November 2018. Their work observed higher persistence of price shocks after the crash, which speculative actions can explain among cryptocurrency traders. The authors also witness the interdependence of bitcoin on other cryptocurrencies and evidence of non-mean reversions, suggesting the existence of chances of further price decreases in cryptocurrencies. Fruehwirt, Hochfilzer, Weydemann, and Roberts (2020) collected data from January 2017 to April 2018 from the Bittrex exchange to conclude that the events in 2017 resulted in a fundamental change, leading to the instability of the cryptocurrency system. Similar to Yaya, Ogbonna, and Olubusoye (2019), this study also reports increased interdependencies of cryptocurrency time series. Eom (2020) added a Korean bitcoin dataset to the most extensively used US data between January 2015 and September 2018 to show that fundamental uncertainty generates more dispersion in heterogeneous beliefs among investors and leads to speculative bubbles. Using a somewhat different data collection technique, Corbet, Lucey, and Yarovaya (2018) sourced data from documented APIs (application programming interfaces) for the period between the 9th of January 2009 and the 9th of November 2017 (3227 data observations in total) to conclude that there are periods of apparent bubble behaviour, with bitcoin almost certainly in a bubble phase at the time of writing their paper. Bianchetti, Ricci, and Scaringi (2018) employ daily data of bitcoin and ethereum covering the period from December 2016 until January 2018 to detect bubbles in their prices. Different estimations reveal that a bitcoin bubble occurs in mid-December 2017 and the first half of January 2018. In terms of ethereum, bubble behaviour appeared mid-June 2017 and a weaker bubble sign was detected around January 12, 2018. Cretarola and Figà-Talamanca (2020) employ a continuous time stochastic model for bitcoin dynamics. They provide evidence that bubbles in digital instruments are connected with the correlation between the market attention factor on bitcoin and bitcoin returns being above a non-negative threshold. Hence, market exuberance is the driving force behind bitcoin bubbles. Wheatley, Sornette, Huber, Reppen, and Gantner (2018) implement a generalised Metcalfe's law in combination with the Log Periodic Power Law Singularity (LPPLS) model to forecast bubbles and crashes in bitcoin markets. This study documents that four bubbles appeared in the bitcoin market, varying heights and lengths. These bubbles took place on the following dates: 28th of August 2012, 10th of April 2013, 5th of December 2013 and 28th of December 2017. Shu and Zhu (2020) support the study of Wheatley, Sornette, Huber, Reppen, and Gantner (2018) by presenting evidence that an adaptive multilevel time series detection methodology based on the LPPLS model and high-frequency data can effectively detect and forecast bubbles. In another vein, Xiong, Liu, and Zhao (2019) justify that bubble estimation based on the production cost by applying the LPPL model shows good forecasting abilities. They predict that the next large bitcoin bubble is expected to occur in the second half of 2020.

Using higher data frequency, Kalyvas, Papakyriakou, Sakkas, and Urquhart (2020) employ tick-level data of bitcoin from September 2011 to December 2018 to examine the drivers

[4] While Donier and Bouchaud (2015) examine the 'order − book liquidity', the 'impact liquidity' and the 'theoretical liquidity', Brauneis, Mestel, Riordan and Theissen (2021) demonstrate that low frequency liquidity measures are relatively good estimates of actual liquidity in cryptocurrency markets.

behind bitcoin price crash risks after taking into account two distinct elements–economic uncertainty and behavioural factors. The authors report that economic uncertainty shows a negative and significant association with bitcoin price risk, implying that the crash risk of bitcoin is low when economic uncertainty is high.

Shu and Zhu (2020) implement an adaptive multilevel time series detection methodology and two levels of bitcoin price data–hourly and half-hourly–to examine the existence of bubbles and monitor the development of the bubbles in the bitcoin price sequence between October 2017 and June 2018. Their analysis shows that the adaptive multilevel time series detection methodology has an outstanding performance in bubble detection and crash forecast, even if the bubble exists in a short period of time. Chaim and Laurini (2019) analyse high-frequency five-minute bitcoin data from January 2013 to September 2018 and confirm the existence of a bubble in bitcoin prices between early 2013 and the middle of 2014, but, interestingly, not in late 2017. Geuder, Kinateder report a similar finding, and Wagner (2019), observes that bubble behaviour is a common and reoccurring characteristic of bitcoin prices in daily data from March 2016 to September 2018. However, a critical time point is identified as the 6th of December 2017, after which neither testing model provides evidence of ongoing bubble behaviour.

Some other studies have contributed to the topic by examining broader datasets that include different cryptocurrencies. Bouri et al. (2019) used daily data of bitcoin, ripple, ethereum, litecoin, nem, dash, and stellar from August 2015 until December 2017 to study co-explosivity in their markets. On the one hand, bitcoin's explosivity is found to lower ripple's explosivity. On the other hand, ethereum's explosivity is reinforced by bitcoin, ripple, nem, and dash, while it receives a negative impact from stellar. In terms of litecoin, there is evidence that bitcoin, ripple, nem, dash, and stellar facilitate its bubbling. It can be noted that contrary to our empirical findings, lower capitalisation currencies prove to be influential towards larger ones. In a similar study, Cagli (2019) examines explosive behaviour in the market values of bitcoin, ethereum, ripple, litecoin, stellar, nem, dash, and monero by collecting daily data for the period between September 2015 and January 2018. Empirical evidence suggests that all cryptocurrencies except for nem present explosive behaviour and exhibit significant pairwise comovement linkages. Chen and Hafner (2019) are the first to examine bubble behaviour in the CRIX index by observing locally volatile price dynamics comparable to speculative bubbles. More recently, Enoksen et al. (2020) detected multiple bubble periods (particularly in 2017 and early 2018) in eight different cryptocurrencies. The authors also find that higher volatility, trading volume and transactions positively relate to bubbles across cryptocurrencies.

Based on much academic research, Kyriazis, Papadamou, and Corbet (2020) survey the academic literature concerning the formation of pricing bubbles in the cryptocurrency markets and suggest that bitcoin appears to have been in a bubble phase since June 2015, while ethereum, nem, stellar, ripple, litecoin, and dash have possessed bubble-related characteristics since September 2015.

The remainder of this paper is organised as follows: Sect. 2 comprises the cryptocurrency data description and data management; Sect. 3 represents the empirical findings; Sect. 4 shows the robustness checks; and Sect. 5 concludes the paper.

2 Cryptocurrency data description and data management

2.1 Cryptocurrency data description

We obtained millisecond data for bitcoin, ethereum, ripple, bitcoin cash, eos, neo, nem, omg, tezos and lisk (described in Appendix B) between the 26th of August and 15th of September, 2018 from Kaiko[5] (Kaiko.com). Kaiko also provides data for approximately 5,000 crypto-to-crypto and crypto-to-fiat currency pairs traded on 28 different exchanges: Btcbox, BTCC, Bittrex, Bitstamp, BTCe, Bitfinex, Bithumb, Bit-Z, bitFlyer, BTC38, BitMEX, Binance, Coinbase, CEX.io, Gatecoin, Gemini, Ethfinex, HitBTC, Huobi, Itbit, Kraken, MtGox, OKEx, OkCoin, Poloniex, Quoine, Yobit and Zaif. Kaiko receives the data by querying Application Programming Interfaces (APIs) provided by the above trading venues. The data is stamped at the millisecond timeframe (reported in Universal Coordinated Time) and presented in the form of a different series of comma-separated files, with each row recording the trade and user ID, transaction type (buy or sell), cryptocurrency volume, transaction fees and a time stamp. In addition, the dataset specifies whether trading orders are initiated by the buyer or the seller and, more specifically, if they are aggressive bids or asks. This particular information is essential for our empirical analysis.

We perform a data-cleaning procedure by aggregating trades following their trade IDs. We remove transactions where bid or ask orders are missing, those that are duplicated and those that have the same identifier for buy and sell orders. Also, we only consider US dollar-denominated trades.

2.2 Cryptocurrency data management

We follow Meade (2002) to model the statistical properties of our millisecond dataset by implementing the following linear ARMA-GARCH model $(1-\phi_1 B-\ldots-\phi_p B^p)(x_t-\theta_0) = \left(1-\theta_1 B\ldots-\theta_q B^q\right)\in_t$, where $V(\in_t|\Theta_{t-1})=\sigma_t^2$; $\sigma_t^2=a_0+a_1\in_{t-1}^2+b\sigma_{t-1}^2$, Θ_t denotes the available information at time period t, while the Student's t_v random variable is represented by $(\in_t/\sigma_t)$. We use the GARCH aspect of the above model to detect the time-varying variance.

The very high presence of no price changes is one of the statistical properties of the millisecond cryptocurrency data. We implemented Meade's (2002) empirical procedure to account for this cryptocurrency market inactivity. We modified the Student's t distribution[6] for the standardised residuals and made their density conditional on market activity:

$$f\left(\frac{\varepsilon_t}{\sigma_t}|\delta_t\right)=\left\{\begin{matrix} p_0\,\dfrac{g_v\left(\frac{\varepsilon_t}{\sigma_t}\right)^{if\ \delta_t=1}}{1-p_{0\ if\ \delta_t=0}} \end{matrix}\right\} \tag{1}$$

[5] We use proper traded prices to execute the topics under our investigation. Alexander and Dakos (2019) suggest that it is very important to use traded data from crypto trading venues rather than data from coin − ranking sites when examining market efficiency, hedging and portfolio optimisation and trading in cryptocurrency markets.

[6] The Student's t distribution represent one–parameter family of curves. The Student's t distribution is usually used in hypothesis examination with respect to the population mean in cases when the population standard deviation is unknown.

where $g_v(\cdot)$ represents the Student's t density function[7]; (ε_t/σ_t) is the Student's t_v random variable; p_0 denotes the population proportion and δ_t measures market inactivity as follows:

$$\delta_t = \begin{Bmatrix} 1 & if|x_t| + |x_{t-1}| = 0 \\ 0 & otherwise \end{Bmatrix} \tag{2}$$

If $\delta_t = 1$, the forecast $\hat{x}_{t+i|t} = 0$ for $i = 1, 2, ...$

The above procedure aims to determine periods of market inactivity and detect the kurtosis and heteroskedasticity when the cryptocurrency market is active.

Considering the large dataset size, another critical statistical issue is Lindley's (1957) paradox. This paradox could lead to the overstatement of statistical significance and a tendency to reject the null hypothesis, even when the posterior odds favour the null. Connolly (1989) addressed Lindley's paradox by developing a procedure for estimating the critical values for t-statistics and F-statistics as a function of the sample size and degrees of freedom. Consequently, the estimated critical values provide a crucial point for when posterior odds favour the alternative hypothesis over the null.

However, in a later study, Szakmary and Keifer (2004) pointed out that the critical t-values equation in the study of Connolly (1989) 'contains an obvious typo and should read':

$$t* = \left[(T-k)\left(T^{1/T} - 1\right)\right]^{0.5} \tag{3}$$

where T represents the sample size and k measures the number of estimated parameters.[8] We conduct large-sample adjustments to the critical t-values to eliminate the statistical significance overstatement. When the absolute value of a regression t-statistic is greater than the t* value of Eq. 3, its absolute value is reduced by the adjustment t*. The null hypothesis is rejected when the estimated standard statistic exceeds the critical value of t*.

3 Empirical findings

3.1 Cryptocurrencies' behaviour during the crash.

Figure 1 shows the decline in the price of bitcoin, ethereum, ripple, bitcoin cash, eos, neo, nem, omg, tezos and lisk on the 5th of September, 2018, and Table 1 represents the descriptive statistics of returns for the ten cryptocurrencies under investigation.

Table 1 shows that the distribution of returns for the ten cryptocurrencies is negatively skewed, indicating that significant negative price changes are more likely than large positive price changes on the 5th of September, 2018. The kurtosis is significantly higher than three for all cryptocurrencies, implying a fat-tailed distribution of returns.

The Jarque-Bera statistics suggest that the null hypothesis of normally distributed returns is rejected for all financial instruments.

[7] Density function represents a statistical articulation illustrating the likelihood of a series of outcomes for a discrete variable, such as a digital currency.

[8] Therefore, we have taken Szakmary and Keifer's (2004) argument into account and presented Eq. 3 as suggested in their study. The T values for the ten cryptocurrencies are as follows: 17,258 observations for bitcoin; 12,366 for ethereum; 9,812 for ripple; 8,799 for bitcoin cash; 6,073 for eos; 2,277 for neo; 2,315 for nem; 2,005 for omg; 1,974 for tezos and 1,244 for lisk. K represents the number of parameters to be estimated, allocated 0 and 1 for the alternative and null hypotheses.

We construct an equally-weighted market portfolio to examine the behaviour of cryptocurrencies in comparison to the market consensus:

$$CMR_{m,t} = \frac{\sum_{i=1}^{N} r_{i,t}}{N} \tag{4}$$

where N measures the number of cryptocurrencies;$CMR_{m,t}$ represents the cryptocurrency market return; and $r_{i,t}$ measures each cryptocurrency's daily return. We estimate each cryptocurrency's daily return as:

$$r_{i,t} = \frac{(P_t - P_{t-1})}{P_{t-1}} \tag{5}$$

where P_t denotes the cryptocurrency price at time t.

Since the main reasons for the cryptocurrency crash are mostly related to bitcoin, we first examine the effect of the more prominent cryptocurrencies on the rest of the market. Similar to Chiang and Zheng (2010), we divide cryptocurrency market returns to differentiate asymmetric herding behaviour in cases when the entire market, including bitcoin, is up or down:

$$CSAD_{m,t} = \alpha + \beta_1(1-D)r_{m,t} + \beta_2 Dr_{m,t} + \beta_3(1-D)r_{m,t}^2 + \beta_4 Dr_{m,t}^2 + u_t \tag{6}$$

where $CSAD_{m,t}$ measures the cross-sectional absolute deviation of returns; $(1-D)$ and D are dummy variables equal to 1 when $r_{m,t} \geq 0$ and $r_{m,t} < 0$, respectively; $r_{m,t}$ represents the cross-sectional average of the N returns at t; and $r_{m,t}^2$ is the cross-sectional average market returns squared term.[9]

The regression results of $CSAD_{m,t}$ on market returns are reported in Table 2 (Panel B) and suggest that the entire cryptocurrency market experiences herding behaviour when prices are decreasing–the coefficient $(D)r_{m,t}^2$ is negative and significant.

We also observe a significant negative value when examining the generalised form $r_{m,t}^2$(Table 2, Panel A). This finding is consistent with several other studies. Leclair (2018) uses five-minute data on the 12 most popular cryptocurrencies and presents significant evidence of increasing herding behaviour in the cryptocurrency markets. Bouri et al. (2019) perform a rolling-window analysis with the daily closing prices of 14 leading cryptocurrencies from 2013 to 2018 and observe significant time-varying herding behaviour, mostly driven by the uncertainty of economic policy. Vidal-Tomás, Ibánes and Farinós (2018) obtained daily data from 65 digital currencies from January, 2015 to December, 2017 and cross-sectional standard deviation of returns as a measure of herding dispersion to analyse the existence of herding behaviour in cryptocurrency markets. This study shows that the most minor cryptocurrencies are herding with the largest ones, and speculators are making decisions based on the performance of the leading digital currencies. Poyser (2018) obtained daily closing prices of the 100 top cryptocurrencies and detected the presence of significant herding behaviour. More recently, Giudici and Polinesi (2021) suggest that bitcoin exchange prices are positively related and, among them, the largest exchanges, such as Bitstamp, drive the prices. King and Koutmos (2021) documented that some cryptocurrency markets show evidence of herding behaviours, while in other markets, the authors show evidence of contrarian-type behaviours.

[9] In Appendix C, we explain both the linear and the non − linear relationship between the cross − sectional absolute deviation of returns (CSAD) and the cryptocurrency market return (CMR). We also provide further explanations on the relationship between the CMR and $r_{m,t}$.

To investigate whether the cryptocurrency market is behaving in the same way as bitcoin, we compute the following regression for a market without bitcoin:

$$CSAD_{wb,t} = \alpha + \beta_1 (1 - D) r_{wb,t} + \beta_2 D r_{wb,t} + \beta_3 (1 - D) r^2_{wb,t} + \beta_4 D r^2_{wb,t} + \beta_5 (1 - D) r^2_{b,t} + \beta_6 D r^2_{b,t} + u_t \quad (7)$$

where $CSAD_{wb,t}$ measures the cross-sectional absolute deviation of returns without bitcoin, using the subscript wb; $(1 - D)r_{wb,t}$, $Dr_{wb,t}$, $(1 - D)r^2_{wb,t}$, and $Dr^2_{wb,t}$ represent the variables without bitcoin; and $(1 - D)r^2_{b,t}$ and $Dr^2_{b,t}$ are the variables with bitcoin included (Vidal-Tomás, Ibánes and Farinós, 2018).

The regression results of $CSAD_{wb,t}$ on market returns differentiating between bitcoin and the rest of the cryptocurrency market (presented in Table 3) suggest that other cryptocurrencies follow the behaviour of bitcoin. This is evident by the significant negative coefficients of both $(1 - D)r^2_{b,t}$ and $(D)r^2_{b,t}$. Moreover, the cryptocurrency market without bitcoin experiences herding behaviour when prices of the financial instruments under investigation are decreasing–the coefficient $(D)r^2_{wb,t}$ is negative and significant. We also observe that the weight of bitcoin in the equally weighted market portfolio increased from − 0.8266 for the entire market, $(D)r^2_{m,t}$ in Table 2, Panel B, to − 0.5725 for the market without bitcoin, $(D)r^2_{wb,t}$ in Table 3. This important finding implies that bitcoin can create the herding phenomenon by itself and that the other cryptocurrencies, therefore, followed the behaviour of bitcoin on the 5th of September, 2018, to trigger the crash. This finding is in line with Yaya, Ogbonna and Olubusoye (2019) and Fruehwirt, Hochfilzer, Weydemann and Roberts (2020) who observe interdependence of bitcoin on other popular cryptocurrencies in the 2107 bitcoin price crash but opposite to Bouri et al. (2019) who report that lower capitalisation currencies prove to be influential towards larger ones.

We next investigate whether the smaller cryptocurrencies affected in the crash behave in the same way as the larger ones by dividing the dataset into two sub-samples. The first sub-sample includes the more prominent cryptocurrencies, while the second sub-sample consists of the smaller ones. We compute the following regression:

$$CSAD_{s,t} = \alpha + \beta_1 (1 - D) r_{s,t} + \beta_2 D r_{s,t} + \beta_3 (1 - D) r^2_{s,t} + \beta_4 D r^2_{s,t} + \beta_5 CSAD_{l,t} + \beta_6 (1 - D) r^2_{l,t} + \beta_7 D r^2_{l,t} + u_t \quad (8)$$

where the s subscript in $CSAD_{s,t}$, $(1 - D)r_{s,t}$, $Dr_{s,t}$, $(1 - D)r^2_{s,t}$ and $Dr^2_{s,t}$ denotes a sub-market with the smaller cryptocurrencies, while the l denotes a sub-market with the larger ones. This model enables the examination of the more minor cryptocurrency behaviour to identify–whether they follow the mean return of their sub-market $\left(r_{s,t}\right)$ or the mean return of the larger ones $\left(r_{l,t}\right)$.

Table 4 shows that the coefficients of $(1 - D)r^2_{l,t}$ and $Dr^2_{l,t}$ are both negative and significant, indicating that the larger digital currencies are driving the remainder of the market. In addition, the coefficient of $CSAD_{l,t}$ is positive and significant, highlighting the dominant influence of the larger cryptocurrency return dispersions in the digital market. Hence, the driving factor behind the crash is the behaviour of the more prominent cryptocurrencies. At the same time, the mean return of the more minor virtual currencies is related to the dynamics of the market to a lesser extent. This is confirmed by the insignificant and positive coefficients of $(1 - D)r^2_{s,t}$ and $(D)r^2_{s,t}$.

While Banerjee (1992) and Yao et al. (2014) explain this with the relatively limited information available about the smaller stocks in traditional financial markets, Nguyen et al. (2020) suggest that bitcoin and litecoin facilitate tail risk when markets are bullish and ethereum and ethereum classic are the significant drivers of tail risk in bearish markets. More recently, Zhang et al. (2021) demonstrated a positive cross-sectional relation between downside risk and future returns in the cryptocurrency market in both portfolio-level analyses and cryptocurrency-level cross-sectional regressions. However, another driver of price crashes could be the impact of operational risk and the related losses, as documented by Giudici and Bilotta (2004), who demonstrate that Bayesian networks represent a valid model for measuring and managing operational risks. In a related study, Fantazzini et al. (2008) implemented copula distributions to model high dimensional operational risks more flexibly, including partial dependence.

Our empirical findings align with the existing literature on the interconnectedness in the cryptocurrency markets. Fry and Cheah (2016) examine cryptocurrency market crashes and demonstrate that in the period of the negative bubble, there is a spillover effect from ripple to bitcoin. Ji, Bouri, Lau and Roubaud (2019) investigated interconnectedness in six prominent cryptocurrencies and reported that bitcoin and litecoin are the main drivers of connected cryptocurrency returns, while Antonakakis et al. (2019) examine the transmission mechanism in nine major cryptocurrencies and shows that ethereum has recently become the leading transmitting cryptocurrency. However, bitcoin maintains its influencing role in the market.

3.2 The activity of CTs and market quality before, during and after the crash.

To investigate whether the activity of CTs triggers the crash, we examine the trading direction relative to permanent price changes and transitory pricing errors of a state space model. When CTs trading is orientated in the opposite direction of the permanent pricing error (negatively correlated with the permanent pricing error) and oriented in the direction of the transitory pricing error (positively correlated with the transitory pricing error), we can conclude that CTs facilitated the crash. In contrast, when CTs trading is orientated in the direction of the permanent pricing error (positively correlated with the permanent pricing error) and oriented in the opposite direction to the transitory pricing error (negatively correlated with the transitory pricing error), we can conclude that CTs did not trigger the crash.

The state space model of the cryptocurrencies can be decomposed into two distinguished parts–permanent and transitory constituents:

$$p_{i,t} = m_{i,t} + s_{i,t} \tag{9}$$

where $p_{i,t}$ represents the (log) mid quote (the average of the bid and ask quote) at a time t for a financial instrument i; $m_{i,t}$ is the permanent component of a martingale type-$m_{i,t} = m_{i,t-1} + w_{i,t}$ with an innovative element $w_{i,t}$ included in the permanent price component; and $s_{i,t}$ represents the transitory price component.

We develop two different state space models to examine the implications of CTs activity on the crash. The first model looks all trading activity denoted CTs^{NET} while the second model analyses the demand and supply components of CTs denoted as CTs^{D} and CTs^{S}. We compute the aggregate model as:

$$w_{i,t} = k_i^{all}\widetilde{CTs}_{i,t}^{NET} + \mu_{i,t} \tag{10}$$

where $\widetilde{CTs}_{i,t}^{NET}$ is the surprise innovation factor in CTs^{NET}, which is the residual of an autoregressive model used to eliminate autocorrelation. We implement the Kalman filter where cryptocurrency price changes,CTs^{NET},CTs^{D} and CTs^{S} are non-zero, in order to estimate the state space model for each digital currency in a trading day for the entire sample period. Table 5 shows the empirical results of the CTs^{NET} related to the permanent price component of the state space model for each financial instrument and the overall space model. Table 6 represents the empirical findings related to the transitory price component of the state space model for each cryptocurrency and the overall space model. We observe that all space models listed in the last row of Table 5 are positively correlated with the permanent price component.

We also observe that all state space models in the last row in Table 6 negatively correlated with the transitory price component. Therefore, CTs trading is orientated in the direction of the permanent pricing error and the opposite direction of the transitory pricing error. These important findings imply that the activity of CTs did not trigger the cryptocurrency crash.

We estimate the values of k and ψ in basis points per \$1,000,000 traded. The value of 0.85 for the overall k coefficient in Table 5 indicates that \$1,000,000 of positive surprise order flow (bid minus ask orders) corresponds to a 0.85 basis points increase in the permanent price component.

The aggregate proportion of permanent price variance $\left(k^{NET} * \sigma\left(CTs^{NET}\right)\right)^2$ estimated at 19.76 basis points is also positively correlated with overall CTs^{NET} order flow. The negative values of ψ coefficients in the transitory price component in Table 6 suggest that CTs trade in the opposite direction of the pricing errors, and therefore the activity of CTs did not trigger the crash. Furthermore, we employ a disaggregated state space model to examine the individual implications of bid and ask cryptocurrency trading orders on the crash. Table 7 shows that CTs bid and ask orders are positively correlated (k^{bid} and k^{ask} values are positive in all ten cryptocurrencies) with price changes in the permanent price component of the state space model. The positive values of k^{ask} and k^{bid} coefficients suggest that trading is conducted in the direction of the permanent pricing errors and therefore did not cause the crash.

At the same time, we find a negative relation between ψ^{bid}, ψ^{ask} and the transitory price component across all ten cryptocurrencies (Table 8), implying that CTs^{bid} and CTs^{ask} trading orders follow the opposite direction of the transitory component of the state space model and therefore did not trigger the crash. A direct comparison between CTs^{bid} and CTs^{ask} trading orders reveals more minor pricing errors for the CTs^{bid} orders, suggesting that significantly more information is incorporated into the bid prices of the ten cryptocurrencies. Omrane, Guesmi, Qianru and Saadi (2021) demonstrate that U.S. macroeconomic news releases exhibit significant influence on jumps in bitcoin and ethereum. However, some studies relate crashes to the risk-bearing ability of intermediaries.[10] We further examine the activity of CTs during the cryptocurrency crash by looking at the risk-bearing ability of CTs. We do that by reviewing the minute-by-minute co-movement between the inventory changes

[10] For example, Huang and Wang (2009, 2010) design an equilibrium model in which market crashes endogenously occur when an unexpected excess of sell orders overcome the insufficient risk − bearing ability of market makers. More recently, Ait−Sahalia and Seglam (2017) relates increases in volatility of prices to tighter inventory bonds for high − frequency traders, highlighting their ability to accommodate increased volatility risk. Alomari et al. (2021) investigate the effect of news and social media sentiments on the stock and bond market volatility and their return dynamic correlation and report that that news sentiments have more pronounced effects on volatility while social media show stronger impacts on the correlation. Ho, Shi and Zhang (2013) confirm the significant impact of firm − specific news sentiment on intraday volatility persistence with firm − specific news sentiment responsible for a greater proportion of overall volatility persistence. Cerchiello and Nicola (2018) implement the Structural Topic Model (STM) to examine the possible evolution of topics obtained from Reuters and Bloomberg and to investigate a causal effect in the diffusion of the news measured by the Granger causality test. The authors report that the temporal dynamics and the spatial differentiation play a role in the news contagion.

of CTs and cryptocurrency prices. Kirilenko, Kyle, Samadi and Tuzun (2017) suggest that intermediaries adjust inventories according to price decreases.

In cases when the risk-bearing ability of intermediaries is overcome, they are somewhat reluctant to hold more inventory without significant price compromise. To investigate the relationship between inventory changes and changes in cryptocurrency prices on the 5th of September, 2018, we adopt an empirically similar approach to Kirilenko, Kyle, Samadi and Tuzun (2017):

$$\Delta y_t = \alpha + \phi \times \Delta y_{t-1} + \delta \times y_{t-1} + \sum_{i=0}^{15} \left[\beta_i \times \Delta p_{t-1}/0.25\right] + \varepsilon_t \tag{11}$$

where y_t denotes the inventories of CTs; Δy_t measures the inventory changes of CTs for each minute; Δp measures price changes between the high-low midpoint of minute t–1 and the high-low midpoint of minute t to accommodate the bid-ask bounce in prices. Similar to Kirilenko, Kyle, Samadi and Tuzun (2017), we convert cryptocurrency price changes into the number of ticks by dividing Δp by 0.25. We estimate the t-statistics using the White (1980) standard errors. Table 9 shows that the regression coefficient of the lagged inventory level is negative, reflecting the mean-reversion of CTs inventory levels. We observe that changes in CTs inventories are positively related to lagged and contemporaneous price changes up to ten lags. CTs inventory changes become negatively associated with cryptocurrency price changes between the 11th and the 15th lagged price changes. This finding is in line with Kirilenko, Kyle, Samadi and Tuzun (2017) but opposite to Hendershott and Seasholes (2007), who documented an entirely negative relationship between the inventories of market makers and price changes. We also investigate whether the observed statistical relationship between CTs inventory changes and cryptocurrency price changes significantly changed during the crash by computing the following regressions:

$$\begin{aligned}\Delta y_t &= \alpha + \phi \Delta y_{t-1} + \delta y_{t-1} + \sum_{i=0}^{15} \left[\beta_i \times p_{t-i}/0.25\right] \\ &\quad + P_t^D \left\{ \alpha^D + \phi^D \Delta y_{t-1} + \delta^D y_{t-1} + \sum_{i=0}^{15} \left[\beta_i^D \times p_{t-i}/0.25\right] \right\}\end{aligned} \tag{12}$$

where P_t^D denotes the price decrease of the ten cryptocurrencies during the crash.

The empirical results of the above regressions presented in Table 10 suggest that all interaction coefficients for CTs during the crash are statistically insignificant.

Therefore, the statistical relationship between CTs inventory changes and price changes of the ten cryptocurrencies did not significantly change during the crash.

We also compute the associated F-test and fail to reject the null hypothesis that the interaction coefficients in Eq. 12 are jointly different from zero, implying that CTs' trading behaviour did not change.

Next, we use different market quality measures to examine the level of liquidity in the days and weeks surrounding the crash. According to Boulton, Braga-Alves, and Kulchania (2014), the bid-ask spread is the primary measure of transaction costs in the microstructure literature. Demsetz (1968) argues that the bid-ask spread compensates investors for supplying liquidity to the market.

We estimate the following three different spread measures:

$$Absolute\,spread = CC\,(a)_{it} - CC\,(b)_{it} \tag{13}$$

where $CC\,(a)_{it}$ and $CC\,(b)_{it}$ represents the ask and bid for cryptocurrency i at time t, respectively.

$$Quoted\,spread\ = \left(CC\,(a)_{it} - CC\,(b)_{it}\right)/CP_{it}x\,100 \tag{14}$$

where CP_{it} represents the cryptocurrency price i at time t.

We also estimate the effective spread because some transactions often occur at a price outside the bid and ask quotes (Lee, 1993).

$$Effective\,spread\ = 2\,x\,S_{it}x\,(P_{it} - M_{it})/M_{it}x\,100 \tag{15}$$

where S_{it} denotes the indicator of trade direction which is set equal to + 1 (− 1) for buy (sell) cryptocurrency trading orders and M_{it} represents the quote midpoint estimated as the average of ask and bid cryptocurrency prices.

However, Lee, Mucklow and Ready (1993) argue that market participants who experience adverse selection can increase spreads and reduce depth, where depth is related to the number of assets a market participant is willing to trade at the best bid and ask quotes. Therefore, we incorporate the average quote depth of the best bid and ask prices on 5th of September, 2018 in our robustness checks:

$$Quote\,depth\ = (Depth_{bid} + Depth_{ask})/2 \tag{16}$$

We report the market quality measures for one day before through one day after the cryptocurrency crash (4th of September–6th of September 2018) in Table 11.

The presented daily spreads are the mean values of the absolute spread, the quoted spread and the effective spread in the millisecond dataset. Panels A, B and C of Table 11 show that the absolute, the quoted, and the effective spreads for bitcoin, ethereum, ripple, bitcoin cash, eos, neo, nem, omg, tezos, and lisk decreased in the days around the crash. All spread measures suggest that trading costs are significantly higher on the 6th of September, the day after the cryptocurrency crash, compared to the 4th of September, the day before the crash. For instance, the average quoted spread of bitcoin is 77% higher on the day after the crash compared to the day of the crash (0.821% and 0.463%, respectively). We obtain similar quoted, effective, and absolute spread results for all other cryptocurrencies. At the same time, we observe that the quote depth for all cryptocurrencies under investigation decreased between the 4th of September 2018 and the 6th of September 2018. Panels A, B and C of Table 11 show that quote depth for the ten cryptocurrencies is significantly lower the day after the crash compared to the day before and the day of the actual crash. In addition, the average turnover, measured as the daily number of crypto assets traded divided by the number of assets outstanding, increased the day after the crash dramatically.

In Table 12, we present the market quality results over ten days before the crash (from the 26th of August to the 4th of September 2018) and compare the absolute, the quoted, and the effective spreads and depth measures to the ten days after the crash (from the 6th of September to the 15th of September 2018). It is evident from Panels A and B of Table 12 that each of the three spread measures has higher values in the ten days after the crash compared to the ten-day period that preceded the crash for bitcoin, ethereum, ripple, bitcoin cash, eos, neo, nem, omg, tezos, and lisk. Furthermore, quote depth decreased significantly, while turnover increased before the cryptocurrency crash.

Overall, we find that changes of inventories of CTs reveal a statistically significant relationship with contemporaneous and lagged changes in cryptocurrency prices. We also observe that this relationship did not change when prices substantially decreased during the crash. Furthermore, our empirical findings suggest that market quality deteriorated during the crash. In addition, this deterioration in market quality is evident beyond the 5th of September 2018, as bid-ask spreads are higher and quote depth is lower in the ten days after the crash compared to the ten days before the cryptocurrency collapse. Such crashes could negatively impact cryptocurrency market participants, investor confidence, and liquidity.

4 Robustness checks

To check the robustness of our results, we divide the dataset into bitcoin-related (standalone) decrease price movements (DPMs) and DPMs that occur simultaneously in several cryptocurrencies (co-DPMs) on the 5th of September, 2018. We define co-DPMs as those that occur in at least two digital currencies. For empirical testing, we use the three different spread measures described in Eqs. (13), (14), (15) and the quote depth in Eq. (16).

Table 13 shows that co-DPMs form 89% of the entire sample (21.6 standalone DPMs and 178.9 co-DPMs). The extremely high DPM occurrence could explain the frequent presence of co-DPMs during the cryptocurrency crash. Table 13 also shows that the average co-DPM includes 8.5 cryptocurrencies, suggesting that the digital currencies affected in the crash are following the behaviour of each other. Trading activity and spread metrics are noticeably different between the two types, with higher volumes and wider spreads recorded during the standalone DPMs.

The spread measures suggest that trading costs were higher during the standalone DPMs due to wider spreads. For example, the average quoted spread is 15% higher for standalone DPMs than co-DPMs (0.184% and 0.159%, respectively). We find similar results for the absolute and the effective spreads. We also find that the quote depth is significantly lower for standalone DPMs than co-DPMs (1719.26 and 1069.14, respectively).

In addition, we use raw data where we did not perform the procedures described in Eqs. 1, 2 and 3 to run another set of robustness checks.[11] The raw data results in Table 14 reveal that co-DPMs form 91% of the entire sample (39.2 standalone DPMs and 424.6 co-DPMs), while the average co-DPM includes 9.1 cryptocurrencies (compared to 8.5 after we perform data management process). These results suggest that the cryptocurrencies affected by the crash are following the behaviour of each other. Similar to Table 13, trading activity and spread values differ between the two types, with higher volume levels and wider spreads recorded during the standalone DPMs. Therefore, the spread measures suggest that trading costs were even higher during the standalone DPMs due to wider spreads when we use raw data. For instance, the average quoted spread is 0.537% for standalone DPMs compared to 0.429% for co-DPMs, with similar trends for the absolute and the effective spreads.

We also observe that the quote depth is significantly lower at 4622.18 for standalone DPMs compared to 3752.58 for co-DPMs. All these findings imply that bitcoin activities dominated the market in the day of the crash, which confirms our main analysis results.

In another set of robustness checks, we examine the co−explosiveness in cryptocurrency market. Bouri, Shahzad and Roubaud (2019) suggest that investigating co-explosivity periods in the cryptocurrency market helps make conclusions on whether the price interaction is strong or weak, which may impact diversification and trading strategies. We compute the following logistic regression to examine co-explosivity in the cryptocurrency market:

$$\log\left(\frac{P(Y=1|X)}{1-P(Y=1|X)}\right) = \beta_0 + \beta_i X_{i,t} + \varepsilon_t \tag{17}$$

[11] Further robustness checks with raw data where we did not perform the procedures described in Eqs. 1, 2 and 3 are available from the authors upon reasonable request.

where the dependent variable is a dummy variable Y that has a value of 1 if $BSADF_{r2,t} \geq cv^{\alpha T}_{r2,t}$(when there is price explosiveness as evidenced by the increase of the BSADF sequence above corresponding critical value) and 0 if $BSADF_{r2,t} \leq cv^{\alpha T}_{r2,t}$; β_0 denotes the constant; $X_{i,t}$ is a set of nine dummy variables, where $i = 1,2\ldots0.9$; each dummy variable implies price explosiveness as shown for the dependent variable, in each of the other remaining nine cryptocurrencies; ε_t represents the error term assumed to be distributed as the logistic distribution.

The backward supremum Augmented Dickey–Fuller (BSADF) test mentioned above is used to determine the starting and ending points of bubble periods. The BSADF test statistics are developed by Phillips, Shi and Yu (2015):

$$BSADF_{r^2}(r_0) = Sup_{r1\in(0,r_2-r_0)} ADF^{r2}_{r_1} \tag{18}$$

where the end of the rolling interval window is set at a fraction r_2 and the actual window size expands from fraction r_0 to fraction r_2. We define the explosiveness periods based on the generalised supremum Augmented Dickey–Fuller (GSADF) test:

$$\begin{aligned} \widehat{r}_e &= \inf_{r_2\in(r_0,1)} \left\{ r_2 : BSADF_{r_2} > cv^{\alpha_T}_{r_2} \right\} \\ \widehat{r}_f &= \inf_{r_2\in\left(\widehat{r}_e,1\right)} \left\{ r_2 : BSADF_{r_2} > cv^{\alpha_T}_{r_2} \right\} \end{aligned} \tag{19}$$

where $cv^{\alpha_T}_{r_2}$ represents the $100(1-\alpha_T)\%$ critical value of the supremum Augmented Dickey–Fuller (SADF) test statistics based on r_2 observations, and α_T has a permanent value of 5%.

Table 15 results reveal that bitcoin price explosivity is the least dependent on the presence of explosivity in other cryptocurrencies. In contrast, the ethereum explosivity occurrence increases with the presence of explosivity in bitcoin, ripple, bitcoin cash and eos. The results also reveal an important observation that the explosivity in bitcoin increases the probability of producing explosivity in all other cryptocurrencies under investigation. Moreover, the explosivity in the more prominent cryptocurrencies such as bitcoin, ethereum, ripple, bitcoin cash and eos facilitates the occurrence of explosivity in the more minor digital currencies like neo, nem, omg, tezos and lisk. We also observe a decrease in the explosiveness affect among some small cryptocurrencies. These observations align with our initial findings that the more prominent cryptocurrencies−and bitcoin in particular−drove the remainder of the market during the crash. This is broadly consistent with Bouri, Shahzad and Roubaud (2019) but opposite the results of Agosto and Cafferata (2020), who observe that bitcoin does not seem more central than the other cryptocurrencies in the process of bubble burst occurrence.

However, one limitation of our study is that we use linear econometric models. Giudici and Raffinetti (2021) suggest the increasing data availability and computational power enable researchers to develop artificial intelligence (AI) machine learning models that are highly predictive. The authors developed a novel AI model based on applying the Shapley approach to Lorenz Zonoid and demonstrate that the model helps access both predictive accuracy and explainability of the explanatory variables in bitcoin prices. Similarly, Lucarelli and Borrotti (2019) demonstrate that the Double Deep Q−learning trading system based on Sharpe ratio reward function represents a profitable approach for trading bitcoin. Hitam and Ismail (2018) obtained a more extensive dataset consisting of bitcoin, ethereum, litecoin, nem, ripple and stellar to show that the Support Vector Machines (SVM) model characterise with higher forecasting accuracy compared to other neural networks and deep learning models. In a similar study, Silva de Souza, Almudhaf, Henrique, Negredo, Ramos, Sobreiro and

Kimura (2019) report that the SVM model can generate conservative bitcoin returns on the risk−adjusted basis, even after taking into account transaction costs. Hong (2021) proposed a new Long Short-Term Memory (LSTM) AI model for automatic cryptocurrency trading, while Buyrukoğlu (2021) suggests that the LSTM and the single−based LSTM models can be employed to obtain reliable analysis results in cryptocurrency trading.

Liashenko, Kravets and Repetskyi (2021) also report that the LSTM model can be used in efficient bitcoin and ethereum exchange rate modelling. Sun, Zhou and Lin (2019) show that their strategy which includes some factors from Alpha101 machine learning algorithm is effective in cryptocurrency trading, while Koker and Koutmos (2020) obtain similar results with their direct reinforcement (DR) model. In a larger-scale study, Liew, Li, Budavári and Sharma (2019) apply data from the most significant 100 cryptocurrency returns between 2015 and 2018 to AI and machine learning algorithms. The authors observe that less volatile cryptocurrencies are slightly more predictable than more volatile ones and suggest that cryptocurrency predictability may be significantly more complex given a set of machine learning algorithms. The study concludes that near-term cryptocurrency markets are semi-strong form efficient, and therefore, day trading cryptocurrencies may be very challenging. Another limitation of our research is the interconnectedness related to the same asset traded on different cryptocurrency exchanges. Giudici and Pagnottoni (2019) implement an extension of Diebold and Yilmaz (2012) econometric connectedness measures to examine the return spillovers in five different bitcoin exchanges during the 2017 increase in prices and the 2018 decline. The authors observe that Bitfinex and Gemini are driving the return spillover transmission, and the interconnectedness of returns decreased significantly before the hype in bitcoin price. At the same time, it settled during the down−market period.

For our final robustness checks, we implemented the BDS (Brock, Dechert, Sheinkman and LeBaron, 1996) statistic tests where the null that the series in question are independent and identically distributed (IID) to investigate whether the linear econometric models described in Eqs. 6, 7, 8, 9, 10, 11 and 12 capture all structures within the data and be representative of the problem space. We believe that this test represents a direct and appropriate examination of model accuracy given a large number of different regression assumptions in our study. In support of this statement, Brock, Dechert, Sheinkman and LeBaron (1996) suggest that their method can be used as a model selection tool and a specification test because the first−order asymptotic distribution of the test statistic is independent of estimation error. Moreover, the authors also suggest that for sample sizes of 500 or more, the test has quite a good size performance and good power against a range of alternatives.

We find this particularly important given our large millisecond dataset. The null hypothesis of the BDS test is that a time series sample comes from a data-generating process that is IID while the alternative hypothesis is unspecified.

The test statistic is based on a measure of spatial correlation in m-dimensional space defined as ‘correlation integral’ (McMillan, 2003) and can be specified as per Kočenda (2010):

$$BDS_{m,T}(d) = T^{0.5}\left[C_{m,T}(d) - C_{1,T}(d)^m\right]/\sigma_{m,T}(d) \tag{20}$$

where σ represents the sample standard deviation of the data, and $C_{m,T}(d)$ denotes the sample correlation integral given ‘embedding dimension’, m, and distance, d. The BDS statistic is asymptotically distributed as a standard normal, $BDS_{m,T} \sim N(0, 1)$ when applied to IID series.

The BDS test p values presented in parentheses in Table 16 reveal that the test statistics are insignificant for all linear regression models under investigation implying that the null hypothesis of IID cannot be rejected. This important finding suggests that our linear regression models capture all structures within the data and are representative of the problem space confirming model accuracy. We can also conclude that the residual errors are normally distributed with constant (homoscedastic) variance.

5 Conclusion

The value of the leading cryptocurrencies significantly decreased on the 5th of September, 2018, creating one of the most prominent digital market crashes. There are three likely reasons behind the crash. One accepted assumption among investors is that the price crash resulted from Goldman Sachs abandoning plans to launch a cryptocurrency trading desk. However, some suggest that this might not reveal the whole story. On the day of the crash a 'whale' with no previously recorded transactions transferred more than 22,100 bitcoins out of the wallet, leading the market to collapse in price. Also, more than 111,000 bitcoins were transferred to the wallets of different trading venues to sell them through the black-market platform Silk Road.

In this study, we investigate what caused the crash using millisecond data of the more prominent cryptocurrencies affected in the crash–bitcoin, ethereum, ripple, bitcoin cash and eos–and the smaller cryptocurrencies–neo, nem, omg, tezos and lisk.

We demonstrate that the entire cryptocurrency market experienced herding behaviour when the prices of the more prominent cryptocurrencies decreased. We observe that bitcoin could facilitate the herding phenomenon on its own, and the other cryptocurrencies followed the behaviour of bitcoin on the 5th of September, 2018.

The more prominent cryptocurrencies such as bitcoin, ethereum, ripple, bitcoin cash and eos drove the remainder of the market during the crash. Therefore, we conclude that the behaviour of the more significant digital currencies, particularly bitcoin, was the driving factor behind the collapse of digital markets. We also examine market quality before, during, and after the crash, including bid−ask spreads and quote depth measures. We find that bid−ask spreads increased, whereas quote depth decreased after the crash. Overall, the deterioration in market quality can be linked directly to the crash, as it could have had the potential to negatively affect investor confidence, cryptocurrency market participation, and liquidity. We also investigate whether the activity of CTs caused the crash by using several state−space models. Our empirical findings show that the trading behaviour of CTs did not trigger the cryptocurrency crash.

Furthermore, we report that significantly more information is incorporated into the bid prices of the ten cryptocurrencies under investigation. An examination of the risk−bearing ability of intermediaries during the market collapse reveals that changes of inventories of CTs are statistically significantly related to contemporaneous and lagged changes in cryptocurrency prices. The regression results indicate that this relationship did not change when cryptocurrency prices significantly decreased during the crash.

Considering this study takes the view that cryptocurrency crash of the 5th of September, 2018 was not the result of an unusual occurrence of events and the actions of CTs, but rather a consequence of herding behaviour among cryptocurrencies triggered by events surrounding bitcoin, we suggest policies to mitigate the negative implication of herding behaviour and address the underlying causes are needed to avoid future cryptocurrency crashes. Based on our empirical findings, we propose the introduction of a single−cryptocurrency circuit breaker or limit up−limit down trading halt (price limit rule). The significant difference between the two mechanisms is that trading is allowed to continue within the price bands for the limit up−limit down tool. In contrast, trading stops with the single−cryptocurrency circuit breaker. For example, a single−cryptocurrency circuit breaker for the largest cryptocurrency bitcoin will estimate the trading threshold and pause trading during market disruptions like a cryptocurrency crash. The aim of a bitcoin circuit breaker is to prevent extreme price movements as it provides a cooling−off period.

The trading threshold of bitcoin should depend on the cryptocurrency reference price, which can be estimated using the average price over the previous five minutes of trading. A trading halt can be triggered after a change of 5% on either side of the average reference price. Therefore, trading can be halted for five minutes when a bitcoin price decline of more than 5% below the average price of the cryptocurrency over the immediately preceding five−minute interval occurs. This should also be the case for a corresponding price increase. Alternatively, the limit up−limit−down mechanism should be able to prevent trade in a cryptocurrency outside upper and lower bonds. The limit up−limit down tool could avoid extreme cryptocurrency price changes due to speculation and provide CTs with more time to obtain and interpret information in a fast−moving digital market. One of the advantages of the limit up−limit down tool is that it does not pause trading activity when there is no significant change in fundamentals. CTs can continue operating at prices within the specified price limit bands even when an extreme price is detected. However, the actual trading process of the digital instrument can continue within the specified limits.

Greenwald and Stein (1991) suggest that circuit breakers play a positive role in reducing transaction risk, which is the risk related to the uncertainty of execution prices. This study also indicates that a circuit breaker could persuade market participants to submit trading orders when current prices do not appropriately present market information.

Lauterbach and Ben-Zion (1993) analysed the trading activities of the Tel-Aviv Stock Exchange during the 1987 market break. They concluded that a trading halt smoothed the price adjustment process and minimized trading order imbalances. At the same time, Kodres and O'Brien (1994) documented that price limits encourage risk sharing in financial markets when price shocks occur before market participants can execute their orders. In a somewhat different study, Anderson and Holt (1997) demonstrate the positive role of a circuit breaker in mitigating unjustified price fluctuations, while Anshuman and Subrahmanyam (1999) suggest that price limits are beneficial in lowering the bid−ask spreads and therefore enhancing liquidity. Similarly, Westerhoff (2003) provides evidence that price limits can reduce price deviations from fundamental values when traders cannot chase price trends.

Data availability The data that support the findings of this study are available from the corresponding author upon request.

Declarations

Conflict of interest The authors have no relevant financial or non−financial interests to disclose. The authors have no competing interests to declare that are relevant to the content of this article. All authors certify that they have no affiliations with or involvement in any organization or entity with any financial interest or non−financial interest in the subject matter or materials discussed in this manuscript. The authors have no financial or proprietary interests in any material discussed in this article.

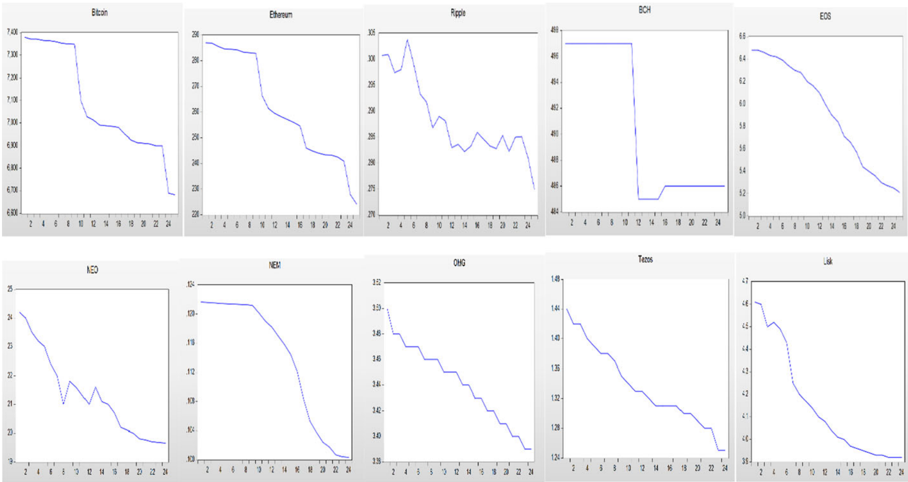

Fig. 1 Price fluctuations of bitcoin, ethereum, ripple, bitcoin cash, eos, neo, nem, omg, tezos and lisk on the 5th of September, 2018. We use raw millisecond data of the ten cryptocurrencies as supplied by the data provider to create a more realistic representation of the dramatic decline in cryptocurrency prices on the 5th of September, 2018. (For a more realistic representation of the event, we use raw millisecond data where we did not apply the econometric data management procedures described in Eqs. 1, 2 and 3.)

Appendix A

Appendix B–Cryptocurrency description

This study considers the five largest−capped cryptocurrencies–bitcoin, ethereum, ripple, litecoin and dash–and two cryptocurrency indices–Crypto Index (CRIX) and CCI30 Crypto Currencies Index.

Bitcoin was the first cryptocurrency that appeared in 2009, providing a solution to the issue of double spending[12] (Nakamoto, 2008). The network is peer-to-peer, and all transactions are conducted between users directly; therefore, there are no third-party entities or financial institutions. Bitcoin transactions are validated by network nodes using cryptography (the $SHA-256$ algorithm) and are stored in a publicly distributed ledger known as a blockchain. Bitcoin is separable to around eight decimal places, but this could be increased further if needed. In economic terms, a single bitcoin can be used at a fractional increment, which can be as small as 0.0000001 bitcoins per single transaction. This particular fractional increment is known as *Satoshi*, named after the developer. As of January, 2018, the current market capitalisation of bitcoin is $191 billion (Bhosale and Mavale, 2018).

Ethereum was first introduced in 2013 by Vitalik Buterin, providing a decentralised platform for smart contracts and distributed applications (DApps) to operate without fraud,

[12] In other words, a bitcoin can be sent securely and one should not be able to spend the same bitcoin again without anyone else being able to facilitate a transaction and without one being able to chargeback the same bitcoin.

Table 1 Descriptive statistics of daily returns for bitcoin, ethereum, ripple, bitcoin cash and eos, neo, nem, omg, tezos and lisk on the 5th of September, 2018

Cryptocurrency	Mean	Median	Min	Max	SK	SD	K	J-B
Bitcoin	0.91	0.78	– 85.55	99.36	– 0.94	17.92	13.17	0.00
Ethereum	0.83	0.55	– 76.76	90.18	– 0.80	16.08	12.04	0.00
Ripple	0.80	0.49	– 60.53	82.81	– 0.67	16.06	9.99	0.00
Bitcoin Cash	0.74	0.47	– 61.86	80.99	– 0.72	15.99	11.82	0.00
Eos	0.61	0.31	– 47.77	63.19	– 0.64	10.43	8.77	0.00
Noe	0.48	0.20	– 30.21	42.55	– 0.51	7.80	4.51	0.00
Nim	0.36	0.14	– 24.97	38.19	– 0.33	6.55	4.08	0.00
Omg	0.27	0.09	– 14.76	31.07	– 0.29	6.21	3.99	0.00
Tezos	0.21	0.05	– 12.52	26.66	– 0.17	4.77	3.16	0.00
Lisk	0.13	0.02	– 10.01	17.99	– 0.09	3.18	3.08	0.00

We estimate each cryptocurrency's daily return as:

$r_{i,t} = \frac{(P_t - P_{t-1})}{P_{t-1}}$ where P_t denotes the cryptocurrency price at time t.

SK skewness, SD standard deviation, K kurtosis, J-B Jarque-Bera test statistics

Table 2 Regression results of $CSAD_{m,\mathrm{t}}$ on market returns for bitcoin, ethereum, ripple, bitcoin cash, eos, neo, nem, omg, tezos and lisk on the 5th of September, 2018

Panel A	
α	0.0673*** (0.0002)
$r_{m,t}$	0.0997*** (0.0240)
$r_{m,t}^2$	– 0.3991*** (0.2570)
$Adj R^2$	0.80
Panel B	
α	0.0711*** (0.0003)
$(1 - D)r_{m,t}$	0.7395*** (0.0274)
$(D)r_{m,t}$	– 0.5336*** (0.0266)
$(1 - D)r_{m,t}^2$	0.8370** (0.8352)
$(D)r_{m,t}^2$	– 0.8266*** (0.1904)
$Adj R^2$	0.81

***Indicates significance at the 1% level; **indicates significance at the 5% level

downtime or intervention from an intermediary. Like bitcoin, this cryptocurrency represents a public platform with open source, blockchain computing and innovative scripting features. *Ether* is the token run on the platform, although the Turing – complete programming language can trade, secure and codify financial derivatives, insurance contracts and many other transactions. As of January, 2018, ethereum has a market capitalisation of approximately $105 billion (Bhosale and Mavale, 2018).

Ripple was introduced in 2012 by Chris Larsen and his company, OpenCoin, to provide instant and affordable international payments. Opposite to bitcoin, this cryptocurrency possesses a consensus ledger that does not require mining from other network users, leading

Table 3 Regression results of $CSAD_{wb,t}$ on market returns differentiating between the larger and the smaller cryptocurrencies on the 5th of September, 2018

Cryptocurrency market on the 5th September, 2018	
α	0.8004*** (0.0012)
$(1-D)r_{wb,t}$	0.7734*** (0.1020)
$(D)r_{wb,t}$	− 0.6881** (0.7053)
$(1-D)r^2_{wb,t}$	0.9906* (0.8571)
$(D)r^2_{wb,t}$	− 0.5725*** (0.0363)
$(1-D)r^2_{b,t}$	0.0689*** (0.0035)
$(D)r^2_{b,t}$	− 0.9007*** (0.0268)
$AdjR^2$	0.82

***Indicates significance at the 1% level; **indicates significance at the 5% level; *indicates significance at the 10% level

Table 4 Regression results of $CSAD_{s,t}$ on market returns differentiating between the larger and the smaller cryptocurrencies on the 5th of September, 2018

Cryptocurrency market on the 5th September, 2018	
α	0.7013*** (0.0010)
$(1-D)r_{s,t}$	0.6903** (0.4830)
$(D)r_{s,t}$	− 0.0478*** (0.0369)
$(1-D)r^2_{s,t}$	2.016 (0.9355)
$(D)r^2_{s,t}$	0.7544 (0.8906)
$CSAD_{l,t}$	0.0882*** (0.0067)
$(1-D)r^2_{l,t}$	− 0.8803*** (0.0105)
$(D)r^2_{l,t}$	− 0.4991*** (0.0283)
$AdjR^2$	0.82

***Indicates significance at the 1% level; **indicates significance at the 5% level

to less computing power and lower network latency. The payment mechanism allows payments to another network user in five seconds, compared to between one and ten minutes in mining − based protocols. Therefore, ripple has a much better likelihood of competing with conventional debit and credit cards point − of − sale transactions.

Moreover, some financial institutions have used this particular cryptocurrency as their main settlement infrastructure technology due to the lack of counterparty credit risk (Phillip, Chan and Peiris, 2018). As of January, 2018, the market capitalisation of ripple is $48 billion (Bhosale and Mavale, 2018).

The name Bitcoin Cash was suggested by the mining pool ViaBTC in July, 2017 and began trading on August, 2017. Bitcoin Cash represents a peer-to-peer online cash system to send money to any recipient in the world, 24 h a day, all year round. Similar to bitcoin, bitcoin cash protocol is restricted to 21 million coins. Compared to conventional payment methods, bitcoin cash provides enhanced anonymity because it is impossible to know who operates the electronic address. The timestamping mining scheme of bitcoin cash is ‘proof − of − work’ (PoW) and its hash function is SHA − 256 (Coinswitch.co).

Table 5 Permanent price component of the Sate Space Model for bitcoin, ethereum, ripple, bicoin cash, eos, neo, nem, omg, tezos and lisk traded on 5th of September, 2018

Permanent price parameters	k^{NET} ($t-$ stat)	$\sigma^2\left(\widetilde{CTs}^{NET}\right)$	$\left(k^{NET} * \sigma\left(\widetilde{CTs}^{NET}\right)\right)^2$ ($t-$ stat)	$\sigma^2\left(w_{i,t}\right)$
Measures	bps/$1,000,000	$1,000,000	bps.2^2	bps.2^2
Bitcoin	0.97 (12.34)	48.88	24.91 (16.77)	470.62
Ethereum	0.82 (11.07)	40.74	22.68 (14.14)	431.09
Ripple	0.70 (10.16)	39.03	18.80 (11.67)	398.66
Bitcoin Cash	0.68 (9.99)	30.99	17.90 (9.51)	380.77
Eos	0.42 (7.51)	26.87	13.85 (8.97)	312.54
Neo	0.38 (5.02)	20.21	9.61 (5.02)	256.91
Nem	0.30 (4.82)	17.55	5.99 (4.81)	216.77
Omg	0.25 (3.32)	10.37	3.14 (2.20)	182.36
Tezos	0.14 (0.3.05)	8.40	1.99 (2.01)	134.68
Lisk	0.09 (2.15)	4.16	0.74 (1.65)	112.94
All	0.85 (7.26)	31.60	19.76 (11.48)	368.33

The model is estimated for each cryptocurrency using CTs variables to decompose the observable historical price $p_{i,t}$ for each cryptocurrency i at time t. into two components: the permanent price component $m_{i,t}$ and the transitory component $s_{i,t}$: $p_{i,t} = m_{i,t} + s_{i,t}$; $m_{i,t} = m_{i,t-1} + w_{i,t}$; $w_{i,t} = k^{NET}\widetilde{CTs}_{i,t}^{NET} + \mu_{i,t}$; $s_{i,t} = \phi s_{i,t-1} + \psi^{NET} CTs_{i,t}^{NET} + \upsilon_{i,t}$.Where $CTs_{i,t}^{NET}$ is the overall net order flow and $\widetilde{CTs}_{i,t}^{NET}$ represent the surprise component of the order flow. We estimate the $t-$ statistics using standard errors double-clustered on the ten digital instruments and millisecond data

EOS represents a decentralised blockchain technology system that allows businesses to develop applications like web − based applications free of transaction fees. The initial platform EOSIO was introduced by a private company called Block.one and was launched as an open − source software product on June 1, 2018. Apart from hosting applications, the other objectives of eos are to implement smart contracts and avoid the scalability issues experienced by bitcoin and ethereum. Eos operates 'proof-of-stake' (PoS) mining mechanism instead of PoW, which enables faster transaction and execution times. Eos allows market participants to participate in blockchain governance and cast votes associated with a fraction of the owner's stake. The programming language used to build eos is WebAssembly, which includes C and C + + (Coinswitch.co).

NEO was introduced as Antshares by Da Hongfei in 2014 and rebranded in 2017. The main aim of neo is to convert traditional financial instruments into decentralised digital ones by using smart contracts. Unlike the above cryptocurrencies, neo is not minable, and there are 100 million tokens. In contrast to other digital currencies based on PoW protocol, neo uses Delegated Byzantine Fault Tolerance (dBFT) mechanism, which can process up to 10,000 transactions per second at much lower electricity costs. The other advantage of neo is that contacts can be written in common programming languages such as Java, Python, C + + , etc., making it less vulnerable to hackers and more accessible to general investors (Coinswitch.co).

NEM, short for New Economic Movement relies on its code built from scratch. Nem aim is to be more technologically advanced blockchain offering easily customizable solutions for

Table 6 Transitory price component of the Sate Space Model for bitcoin, ethereum, ripple, bicoin cash, eos, neo, nem, omg, tezos and lisk traded on 5th of September, 2018

Transitory price parameters	ϕ(t-stat)	ψ^{NET}(t-stat)	$\sigma^2\left(\widetilde{CTs}^{NET}\right)$	$\left(\psi^{NET} * \sigma\left(\widetilde{CTs}^{NET}\right)\right)^2$ (t-stat)	$\sigma^2(s_{i,t})$
Measures	bps/$1,000,000	$1,000,000	$1,000,000	bps.2^2	bps.2^2
Bitcoin	– 0.41 (– 0.20)	– 0.36 (– 7.18)	– 1.93	– 10.76 (– 16.70)	– 251.62
Ethereum	– 0.37 (– 0.15)	– 0.33 (– 5.21)	– 1.87	– 9.81 (– 12.09)	– 248.07
Ripple	– 0.28 (– 0.12)	– 0.25 (– 4.44)	– 1.70	– 9.50 (– 10.14)	– 221.88
Bitcoin Cash	– 0.26 (– 0.09)	– 0.28 (– 5.01)	– 1.79	– 9.89 (– 11.21)	– 235.74
Eos	– 0.18 (– 0.07)	– 0.21 (– 3.99)	– 1.53	– 6.72 (– 8.17)	– 181.50
Neo	– 0.13 (– 0.08)	– 0.15 (– 2.27)	– 1.42	– 5.80 (– 7.43)	– 160.55
Nem	– 0.09 (– 0.05)	– 0.12 (– 2.05)	– 1.30	– 4.46 (– 5.99)	– 148.23
Omg	– 0.06 (– 0.03)	– 0.09 (– 1.88)	– 1.22	– 4.05 (– 5.77)	– 133.80
Tezos	– 0.04 (– 0.02)	– 0.08 (– 0.90)	– 1.16	– 3.29 (– 4.88)	– 117.66
Lisk	– 0.03 (– 0.02)	– 0.06 (– 0.84)	– 0.96	– 2.17 (– 3.06)	– 100.54
All	– 0.24 (– 0.15)	– 0.29 (– 1.67)	– 1.58	– 8.83 (– 6.91)	– 212.83

The model is estimated for each cryptocurrency using CTs variables to decompose the observable historical price $p_{i,t}$ for each cryptocurrency i at time t. into two components: the permanent price component $m_{i,t}$ and the transitory component $s_{i,t}$: $p_{i,t} = m_{i,t} + s_{i,t}$; $m_{i,t} = m_{i,t-1} + w_{i,t}$; $w_{i,t} = k^{NET}\widetilde{CTs}_{i,t}^{NET} + \mu_{i,t}$; $s_{i,t} = \phi s_{i,t-1} + \psi^{NET} CTs_{i,t}^{NET} + \upsilon_{i,t}$

Where $CTs_{i,t}^{NET}$ is the overall net order flow and $\widetilde{CTs}_{i,t}^{NET}$ represent the surprise component of the order flow. We estimate the t-statistics using standard errors double-clustered on the ten digital instruments and millisecond data

Table 7 Permanent price parameters of the disaggregated Sate Space Model for bitcoin, ethereum, ripple, bicoin cash, eos, neo, nem, omg, tezos and lisk traded on 5th of September, 2018

Permanent price parameters	k^{bid} (t-stat)	k^{ask} (t-stat)	$\sigma^2\left(\widetilde{CTs}^{bid}\right)$	$\sigma^2\left(\widetilde{CTs}^{ask}\right)$	$\left(k^{bid} * \sigma\left(\widetilde{CTs}^{bid}\right)\right)^2$ (t-stat)	$\left(k^{ask} * \sigma\left(\widetilde{CTs}^{ask}\right)\right)^2$ (t-stat)	$\sigma^2(w_{i,t})$
Measures	bps/$1,000,000	bps/$1,000,000	$1,000,000	/$1,000,000	bps.2^2	bps.2^2	bps.2^2
Bitcoin	51.83 (19.80)	48.09 (16.45)	2.23	1.12	72.19 (26.51)	58.61 (21.25)	647.53
Ethereum	47.66 (15.16)	43.28 (14.44)	1.98	1.01	70.02 (21.91)	52.01 (19.82)	589.04
Ripple	39.87 (12.26)	37.18 (11.31)	1.83	0.80	60.83 (18.99)	46.87 (17.77)	512.24
Bitcoin cash	41.55 (13.88)	39.87 (10.11)	1.90	0.87	68.88 (20.18)	50.31 (20.29)	555.93
Eos	30.21 (9.45)	27.73 (8.16)	1.56	0.71	57.51 (18.80)	45.52 (18.83)	406.81
Neo	24.33 (5.02)	21.76 (4.93)	1.44	0.52	42.99 (16.66)	39.99 (14.19)	387.92
Nem	22.99 (4.81)	18.54 (4.11)	1.30	0.40	36.07 (14.42)	28.84 (11.03)	351.08
Omg	17.24 (4.03)	14.90 (3.87)	1.27	0.32	28.88 (12.42)	20.32 (9.76)	283.77
Tezos	13.67 (3.88)	10.42 (3.05)	1.15	0.25	21.77 (10.71)	16.43 (7.70)	266.60
Lisk	10.81 (2.95)	7.62 (2.44)	1.08	0.16	18.52 (9.99)	12.42 (6.53)	194.99
All	32.26 (7.73)	27.41 (6.46)	1.62	0.94	60.81 (19.72)	43.85 (13.66)	470.68

The model is estimated for each cryptocurrency using CTs variables to decompose the observable historical price $p_{i,t}$ for each cryptocurrency i at time t into two components: the permanent price component $m_{i,t}$ and the transitory component $s_{i,t}$: $p_{i,t} = m_{i,t} + s_{i,t}$; $m_{i,t} = m_{i,t-1} + w_{i,t}$;$w_{i,t} = k_i^{bid}\widetilde{CTs}_{i,t}^{bid} + k_i^{ask}\widetilde{CTs}_{i,t}^{ask} + \mu_{i,t}$;$s_{i,t} = \phi s_{i,t-1} + \psi_i^{bid} CTs_{i,t}^{bid} + \psi_i^{ask} CTs_{i,t}^{ask} + \upsilon_{i,t}$.Where $CTs_{i,t}^{bid}$ and $CTs_{i,t}^{ask}$ represent bid and ask order flows; $\widetilde{CTs}_{i,t}^{bid}$ and $\widetilde{CTs}_{i,t}^{ask}$ are the surprise components in those order flows. We estimate the t-statistics using standard errors double-clustered on the ten digital instruments and millisecond data

Table 8 Temporary price parameters of the disaggregated Sate Space Model for bitcoin, ethereum, ripple, bicoin cash, eos, neo, nem, omg, tezos and lisk traded on 5th of September, 2018

Transitory price parameters	ϕ(t-stat)	ψ^{bid}(t-stat)	ψ^{ask}(t-stat)	$\sigma^2\left(\widetilde{CTs}^{bid}\right)$	$\sigma^2\left(\widetilde{CTs}^{ask}\right)$	$\left(\psi^{bid} * \sigma\left(\widetilde{CTs}^{bid}\right)\right)^2$ (t-stat)	$\left(\psi^{ask} * \sigma\left(\widetilde{CTs}^{ask}\right)\right)^2$ (t-stat)	$\sigma^2(s_{i,t})$
Measures	bps/$1,000,000	bps/$1,000,000	bps/$1,000,000	$1,000,000	$1,000,000	bps.2^2	bps.2^2	bps.2^2
Bitcoin	− 0.87 (− 3.17)	− 31.27 (− 8.77)	− 19.68 (− 5.92)	− 1.84	− 0.98	− 49.90 (− 16.81)	− 30.10 (− 12.33)	− 513.88
Ethereum	− 0.83 (− 2.90)	− 28.88 (− 7.99)	− 18.69 (− 5.03)	− 1.77	− 0.83	− 37.06 (− 13.28)	− 22.81 (− 9.32)	− 401.09
Ripple	− 0.60 (− 1.96)	− 22.90 (− 6.61)	− 16.52 (− 4.84)	− 1.52	− 0.72	− 30.18 (− 10.19)	− 18.44 (− 5.99)	− 355.68
Bitcoin cash	− 0.67 (− 1.83)	− 26.85 (− 5.01)	− 17.05 (− 4.90)	− 1.66	− 0.76	− 35.81 (− 12.27)	− 19.03 (− 6.05)	− 372.34
Eos	− 0.42 (− 1.25)	− 19.80 (− 3.77)	− 12.88 (− 2.59)	− 1.04	− 0.55	− 23.66 (− 8.98)	− 15.07 (− 4.81)	− 299.19
Neo	− 0.26 (− 0.99)	− 16.99 (− 2.89)	− 9.61 (− 2.03)	− 0.86	− 0.48	− 17.53 (− 6.61)	− 13.14 (− 4.05)	− 246.78
Nem	− 0.17 (− 0.72)	− 12.42 (− 2.67)	− 6.55 (− 1.74)	− 0.69	− 0.31	− 11.82 (− 4.19)	− 8.19 (− 2.90)	− 178.05
Omg	− 0.12 (− 0.66)	− 10.19 (− 2.07)	− 6.01 (− 1.40)	− 0.42	− 0.25	− 7.23 (− 2.88)	− 5.51 (− 2.12)	− 144.62
Tezos	− 0.09 (− 0.25)	− 8.72 (− 1.93)	− 4.18 (− 1.21)	− 0.27	− 0.20	− 4.17 (− 1.80)	− 2.88 (− 1.77)	− 131.03

Table 8 (continued)

Transitory price parameters	ϕ(t-stat)	ψ^{bid}(t-stat)	ψ^{ask}(t-stat)	$\sigma^2\left(\widetilde{CTs}^{bid}\right)$	$\sigma^2\left(\widetilde{CTs}^{ask}\right)$	$\left(\psi^{bid} * \sigma\left(\widetilde{CTs}^{bid}\right)\right)^2$ (t-stat)	$\left(\psi^{ask} * \sigma\left(\widetilde{CTs}^{ask}\right)\right)^2$ (t-stat)	$\sigma^2(s_{i,t})$
Lisk	− 0.06 (− 0.12)	− 5.89 (− 1.42)	− 2.80 (− 0.99)	− 0.18	− 0.11	− 2.04 (− 1.27)	− 1.52 (− 0.93)	− 102.35
All	− 0.62 (− 1.01)	− 18.62 (− 3.86)	− 14.95 (− 4.18)	− 1.03	− 0.58	− 28.83 (− 4.19)	− 18.71 (− 3.79)	− 303.67

The model is estimated for each cryptocurrency using CTs variables to decompose the observable historical price $p_{i,t}$ for each cryptocurrency i at time t into two components: the permanent price component $m_{i,t}$ and the transitory component $s_{i,t}$: $p_{i,t} = m_{i,t} + s_{i,t}$; $m_{i,t} = m_{i,t-1} + w_{i,t}$;$w_{i,t} = k_i^{bid}\widetilde{CTs}_{i,t}^{bid} + k_i^{ask}\widetilde{CTs}_{i,t}^{ask} + \mu_{i,t}$;$s_{i,t} = \phi s_{i,t-1} + \psi_i^{bid} CTs_{i,t}^{bid} + \psi_i^{ask} CTs_{i,t}^{ask} + \upsilon_{i,t}$.Where $CTs_{i,t}^{bid}$ and $CTs_{i,t}^{ask}$ represent bid and ask order flows; $\widetilde{CTs}_{i,t}^{bid}$ and $\widetilde{CTs}_{i,t}^{ask}$ are the surprise components in those order flows. We estimate the t-statistics using standard errors double-clustered on the ten digital instruments and millisecond data

Table 9 Net prices and CTs' holdings of bitcoin, ethereum, ripple, bicoin cash, eos, neo, nem, omg, tezos and lisk traded on 5th of September, 2018

Variable	$\Delta NP\ CTs$
Intercept	– 3.18 (– 6.77)
$\Delta NP\ CTs_{t-1}$	– 0.04 (– 0.86)
$NP\ CTs_{t-1}$	– 0.03 (– 4.25)
ΔP_t	51.97 (21.44)
ΔP_{t-1}	26.70 (16.83)
ΔP_{t-2}	22.68 (13.05)
ΔP_{t-3}	20.99 (12.70)
ΔP_{t-4}	20.04 (11.82)
ΔP_{t-5}	18.55 (9.78)
ΔP_{t-6}	15.32 (8.74)
ΔP_{t-7}	14.08 (6.27)
ΔP_{t-8}	10.26 (5.80)
ΔP_{t-9}	8.68 (5.24)
ΔP_{t-10}	5.99 (3.63)
ΔP_{t-11}	– 0.18 (– 0.25)
ΔP_{t-12}	– 0.87 (– 1.26)
ΔP_{t-13}	– 1.36 (– 2.80)
ΔP_{t-14}	– 2.09 (– 2.93)
ΔP_{t-15}	– 3.41 (– 4.02)
Adj. R^2	0.73

This table shows the computed coefficients for the regression: $\Delta y_t = \alpha + \phi \times \Delta y_{t-1} + \delta \times y_{t-1} +_{i=0}^{15} \left[\beta_i \times \Delta p_{t-1}/0.25\right] + \varepsilon_t$. Change in holdings of CTs represents the dependent variable. Price changes are presented in ticks. *NP* denotes net price of the ten digital instruments. The sampling frequency is at the millisecond timeframe. We estimate the t-statistics reported in parentheses by using the White (1980) estimator

different purposes. Like noe, nem cannot be mined, substantially reducing the energy and time required to process a transaction. The processing time of 4,000 transactions per second makes nem faster than Visa and MasterCard. Nem can be generated through a process known as 'harvesting', and all 9 billion coins are currently in supply. Harvesting represents a process when a transaction is processed on the platform; the first computer to see and verify it will inform other users, creating a block. Moreover, nem uses a 'proof-of-importance' (PoI) method, which is different than PoW and PoS. PoI method assigns more block rewards to users who own more tokens and actively participate in the network (Coinswitch.co).

OmiseGo (OMG) is an ethereum based open-source payment platform developed in Thailand by Jun Hasegawa in 2013. Omg aims to offer banking and financial services worldwide. These include credit and debit card transactions, currency conversions, remittance services, etc. All financial services are done through the omg currency, which can be converted to fiat money, loyalty points or tokens, depending on the type of transaction. The total omg supply is 140 million tokens.

Tezos (TEZ) is the first self-amending cryptocurrency created by Arthur Breitman after publishing two white papers in 2014. Tezos represents a secure, innovative contract platform

Table 10 The relationship between CTs inventory changes and cryptocurrency price changes for bitcoin, ethereum, ripple, bicoin cash, eos, neo, nem, omg, tezos and lisk traded on 5th of September, 2018

Variable	ΔNP *CTs*	Variable (cont)
Intercept	– 4.80 (– 7.42)	Intercept^D
ΔNP_{t-1}	– 0.013 (– 0.61)	ΔNP^D_{t-1}
NP_{t-1}	– 0.014 (– 0.70)	NP^D_{t-1}
ΔP_t	56.99 (21.16)	ΔP^D_t
ΔP_{t-1}	28.77 (14.05)	ΔP^D_{t-1}
ΔP_{t-2}	27.94 (12.73)	ΔP^D_{t-2}
ΔP_{t-3}	23.55 (10.09)	ΔP^D_{t-3}
ΔP_{t-4}	20.25 (8.66)	ΔP^D_{t-4}
ΔP_{t-5}	19.57 (7.51)	ΔP^D_{t-5}
ΔP_{t-6}	17.88 (7.04)	ΔP^D_{t-6}
ΔP_{t-7}	15.90 (6.25)	ΔP^D_{t-7}
ΔP_{t-8}	14.87 (6.06)	ΔP^D_{t-8}
ΔP_{t-9}	9.70 (4.17)	ΔP^D_{t-9}
ΔP_{t-10}	8.46 (3.43)	ΔP^D_{t-10}
ΔP_{t-11}	– 0.25 (– 0.73)	ΔP^D_{t-11}
ΔP_{t-12}	– 0.98 (– 1.79)	ΔP^D_{t-12}
ΔP_{t-13}	– 1.83 (– 2.80)	ΔP^D_{t-13}
ΔP_{t-14}	– 3.99 (– 4.01)	ΔP^D_{t-14}
ΔP_{t-15}	– 5.65 (– 4.74)	ΔP^D_{t-15}
Adj. R^2	0.74	

This table shows the computed coefficients for the regression: $\Delta y_t = \alpha + \phi \Delta y_{t-1} + \delta y_{t-1} +_{i=0}^{15} \left[\beta_i \times p_{t-i}/0.25\right] + P_t^D \left\{\alpha^D + \phi^D \Delta y_{t-1} + \delta^D y_{t-1} +_{i=0}^{15} \left[\beta_i^D \times p_{t-i}/0.25\right]\right\}$. P_t^D represents a dummy variable related to price decrease of the ten cryptocurrencies on the 5th of September, 2018. Change in holdings of CTs represents the dependent variable. Price changes are presented in ticks. *NP* denotes net price of the ten digital instruments. The sampling frequency is at the millisecond timeframe. We estimate the t-statistics reported in parentheses by using the White (1980) estimator

with a built-in consensus mechanism. The protocol of this digital currency can evolve and integrate new information over time. Tesoz uses PoS system, which does not involve mining and significant amounts of electricity consumption–the primary operational process is called 'baking' instead of mining. Bakers in this blockchain system devote deposits and receive rewards for developing and publishing blocks. An innovative feature of the platform is the involvement of all stakeholders towards governing Tesoz. Stakeholders can vote on changes to the main protocol or even the entire voting policy (Tezos.com).

Lisk was developed by Max Kordek and Oliver Beddows and launched in early 2016. Lisk is a decentralised app system that enables users to design apps in Java, making it much more accessible to the public. Lisk uses sidechains technology and Sowtware Development

Table 11 Market quality measures before, during and after the cryptocurrency crash for bitcoin, ethereum, ripple, bicoin cash, eos, neo, nem, omg, tezos and lisk

Panel A-4th September	Absolute spread	Quoted spread	Effective spread	Quote depth	Turnover %
Bitcoin	0.196	0.478	0.380	4835.882	3.187
Ethereum	0.164	0.440	0.313	4226.006	2.903
Ripple	0.099	0.391	0.261	2716.993	1.467
Bitcoin cash	0.074	0.255	0.224	1934.264	1.120
Eos	0.061	0.201	0.116	1355.027	1.080
Neo	0.044	0.177	0.074	926.180	0.096
Nem	0.028	0.149	0.055	790.178	0.054
Omg	0.019	0.142	0.029	511.163	0.021
Tezos	0.008	0.121	0.014	217.199	0.014
Lisk	0.006	0.109	0.005	99.103	0.009
Panel B-5th September					
Bitcoin	0.182	0.463	0.365	4699.004	3.776
Ethereum	0.151	0.426	0.290	3884.465	3.005
Ripple	0.086	0.382	0.204	2390.774	1.888
Bitcoin cash	0.062	0.237	0.193	1624.193	1.568
Eos	0.042	0.197	0.105	1008.255	1.111
Neo	0.038	0.164	0.051	773.109	0.102
Nem	0.020	0.133	0.028	600.128	0.063
Omg	0.015	0.128	0.015	480.083	0.038
Tezos	0.004	0.105	0.006	156.104	0.028
Lisk	0.001	0.102	0.002	71.190	0.018
Panel C-6th September					
Bitcoin	0.662	0.821	0.777	3116.108	4.126
Ethereum	0.630	0.799	0.715	2004.374	3.572
Ripple	0.311	0.711	0.688	1873.006	2.210
Bitcoin cash	0.287	0.664	0.569	1004.526	1.999
Eos	0.216	0.588	0.466	777.172	1.773
Neo	0.188	0.552	0.337	336.124	0.887
Nem	0.173	0.424	0.220	362.199	0.552
Omg	0.126	0.411	0.167	279.073	0.115
Tezos	0.099	0.389	0.121	75.110	0.099
Lisk	0.083	0.366	0.093	32.175	0.064

This table shows the market quality measures for all cryptocurrencies under investigation traded on 4th, 5th and 6th of September, 2018. We estimate the absolute spread as: $Absolute\ spread = CC\,(a)_{it}–CC\,(b)_{it}$.
where $CC\,(a)_{it}$ and $CC\,(b)_{it}$ represents the ask and bid for cryptocurrency i at time t, respectively. We estimate the quoted spread as: $Quoted\ spread = (CC\,(a)_{it}–CC\,(b)_{it})\ /\ CP_{it}\ \times 100$.
where CP_{it} represents the cryptocurrency price i at time t. We also estimate the effective spread as:
Effective spread $= 2 \times S_{it}$ x $(P_{it}–M_{it})$ / M_{it} x 100.
where S_{it} denotes the indicator of trade direction which is set equal to + 1 (− 1) for buy (sell) cryptocurrency trading orders and M_{it} represents the quote midpoint estimated as the average of ask and bid cryptocurrency prices. We calculate the quoted depth as: $Quote\ depth = (Depth_{bid} + Depth_{ask})\ /\ 2$. We report the turnover as the daily number of cryptocurrencies traded divided by the number of cryptocurrencies outstanding (in percentage). The presented daily spreads are the mean values of the absolute spread, the quoted spread and the effective spread in the millisecond dataset

Table 12 Market quality measures ten-days before and ten-days after the cryptocurrency crash for bitcoin, ethereum, ripple, bicoin cash, eos, neo, nem, omg, tezos and lisk

Panel A:26th August-4th September	Absolute spread	Quoted spread	Effective spread	Quote depth	Turnover %
Bitcoin	0.215	0.582	0.446	5374.299	6.887
Ethereum	0.189	0.503	0.412	4604.172	5.471
Ripple	0.121	0.412	0.323	3545.006	3.822
Bitcoin cash	0.088	0.290	0.281	2257.016	2.713
Eos	0.073	0.203	0.163	1506.002	2.006
Neo	0.059	0.184	0.104	1003.777	1.850
Nem	0.040	0.173	0.073	886.002	1.477
Omg	0.027	0.152	0.047	636.809	1.102
Tezos	0.016	0.133	0.028	376.929	1.004
Lisk	0.012	0.118	0.014	121.535	0.096
Panel B: 6th September-15th September					
Bitcoin	0.286	0.699	0.577	4722.106	4.663
Ethereum	0.207	0.578	0.548	3770.274	3.997
Ripple	0.172	0.498	0.466	2999.728	1.906
Bitcoin cash	0.096	0.313	0.402	1836.152	1.535
Eos	0.085	0.280	0.256	1283.028	1.276
Neo	0.071	0.204	0.249	743.204	1.003
Nem	0.066	0.199	0.184	524.726	0.851
Omg	0.045	0.186	0.126	423.116	0.088
Tezos	0.036	0.167	0.097	226.109	0.046
Lisk	0.024	0.145	0.066	96.277	0.023

This table shows the market quality measures for all cryptocurrencies under investigation traded in two different periods–between 26th of August and 4th of September, 2018 and between 6th of September 15th of September, 2018. We estimate the absolute spread as: $Absolute\ spread = CC\,(a)_{it} - CC\,(b)_{it}$.
where $CC\,(a)_{it}$ and $CC\,(b)_{it}$ represents the ask and bid for cryptocurrency i at time t, respectively. We estimate the quoted spread as: $Quoted\ spread = (CC\,(a)_{it} - CC\,(b)_{it})\ /\ CP_{it} \times 100$
where CP_{it} represents the cryptocurrency price i at time t. We also estimate the effective spread as:
Effective spread $= 2 \times S_{it} \times (P_{it} - M_{it})\ /\ M_{it} \times 100$
where S_{it} denotes the indicator of trade direction which is set equal to + 1 (− 1) for buy (sell) cryptocurrency trading orders and M_{it} represents the quote midpoint estimated as the average of ask and bid cryptocurrency prices. We calculate the quoted depth as: $Quote\ depth = (Depth_{bid} + Depth_{ask})\ /\ 2$. We report the turnover as the daily number of cryptocurrencies traded divided by the number of cryptocurrencies outstanding (in percentage)

Kit (SDK), allowing the users to create DApps and individual blockchains within the central platform.

Unlike most other cryptocurrencies, Lisk does not represent a digital form of money that retailers will accept as payment but instead as a currency for users of the platform. Lisk uses PoS protocol and can be mined, but the mining process differs from bitcoin. In contrast to bitcoin, there is no cap on the maximum number of lisk coins (Coinswitch.co).

Table 13 Standalone and co-DPMs on the 5th of September, 2018

	Bitcoin (standalone)		Co-DPMs	
	mean	std.dev	mean	std.dev
Number of DPMs	21.6		178.9	
Number of cryptocurrencies			8.5	
Absolute return %	0.67	0.34	0.51	0.28
Traded volume	179.24	121.26	162.38	103.56
Absolute spread	0.062	0.136	0.051	0.121
Quoted spread	0.184	0.927	0.159	0.783
Effective spread	0.105	0.217	0.094	0.199
Quoted depth	1719.26	11.36	1069.14	8.92

This table divides DPMs into standalone (bitcoin) and co-DPMs, with the latter category detecting DPMs that occur simultaneously in several cryptocurrencies. We estimate the absolute spread as: *Absolute spread* = $CC\ (a)_{it}$–$CC\ (b)_{it}$
where $CC\ (a)_{it}$ and $CC\ (b)_{it}$ represents the ask and bid for cryptocurrency *i* at time *t*, respectively. We estimate the quoted spread as: *Quoted spread* = $(CC\ (a)_{it}–CC\ (b)_{it})\ /\ CP_{it} \times 100$
where CP_{it} represents the cryptocurrency price *i* at time *t*. We also estimate the effective spread as:
Effective spread = $2 \times S_{it}$ x $(P_{it}–M_{it})\ /\ M_{it}$ x 100
where S_{it} denotes the indicator of trade direction which is set equal to + 1 (− 1) for buy (sell) cryptocurrency trading orders and M_{it} represents the quote midpoint estimated as the average of ask and bid cryptocurrency prices. We calculate the quoted depth as: *Quote depth* = $(Depth_{bid} + Depth_{ask})/2$

Table 14 Standalone and co-DPMs on the 5th of September, 2018 with raw data

	Bitcoin (standalone)		Co-DPMs	
	mean	std.dev	mean	std.dev
Number of DPMs	39.2		424.6	
Number of cryptocurrencies			9.1	
Absolute return %	0.94	0.66	0.78	0.49
Traded volume	622.18	446.03	403.57	397.15
Absolute spread	0.183	0.316	0.124	0.412
Quoted spread	0.537	1.015	0.429	0.993
Effective spread	0.682	0.446	0.214	0.307
Quoted depth	4622.18	37.72	3752.58	23.16

For robustness checks we use raw data where we did not perform the procedures described in Eqs. 1, 2 and 3. This table divides DPMs into standalone (bitcoin) and co-DPMs, with the latter category detecting DPMs that occur simultaneously in several cryptocurrencies. We estimate the absolute spread as: *Absolute spread* = $CC\ (a)_{it}$–$CC\ (b)_{it}$
where $CC\ (a)_{it}$ and $CC\ (b)_{it}$ represents the ask and bid for cryptocurrency *i* at time *t*, respectively. We estimate the quoted spread as: *Quoted spread* = $(CC\ (a)_{it}–CC\ (b)_{it})\ /\ CP_{it} \times 100$
where CP_{it} represents the cryptocurrency price *i* at time *t*. We also estimate the effective spread as:
Effective spread = $2 \times S_{it}$ x $(P_{it}–M_{it})\ /\ M_{it}$ x 100
where S_{it} denotes the indicator of trade direction which is set equal to + 1 (− 1) for buy (sell) cryptocurrency trading orders and M_{it} represents the quote midpoint estimated as the average of ask and bid cryptocurrency prices. We calculate the quoted depth as: *Quote depth* = $(Depth_{bid} + Depth_{ask})\ /\ 2$

Table 15 Logistic regression results using dummies of cryptocurrency explosivity as dependent and independent variables for bitcoin, ethereum, ripple, bitcoin cash, eos, neo, nem, omg, tezos and lisk on the 5th of September, 2018

Crypto	Bitcoin	Ethereum	Ripple	Bitcoin Cash	Eos	Noe	Nim	Omg	Tezos	Lisk
Bitcoin		2.693***	4.006***	1.120***	4.157***	5.137***	2.362***	6.003***	3.268***	5.239***
Ethereum			2.183***	2.997***	3.162**	4.266**	2.889***	1.988***	2.616***	4.103***
Ripple		4.888***		5.022**	5.434***	4.809***	4.535**	3.177**	3.816***	5.163**
Bitcoin Cash		3.709***	1.655**		3.551**	2.160*	3.260***	2.314***	4.225**	5.727***
Eos		6.115**	3.768*	6.077***		1.288**	2.007***	4.261**	6.263***	7.172***
Noe							1.290***	3.288***	2.099***	2.879***
Nim						1.773***		2.259***	3.002**	1.277**
Omg						– 2.302**	– 1.358***		4.023***	3.363*
Tezos						3.126*	1.816**	– 2.114**		4.272***
Lisk						– 1.365***	– 2.349***	– 1.238***	– 1.206**	
C	– 2.014***	– 4.827***	– 6.250***	– 3.799***	– 7.152***	– 7.996***	– 9.131***	– 11.890**	– 15.142***	– 17.528**
McFadden R^2	0.057***	0.283***	0.516***	0.097***	0.826***	0.885***	0.735***	0.816**	0.924***	0.977**

***indicates significance at the 1% level; **indicates significance at the 5% level; *indicates significance at the 10% level

This table shows the results from the following logistic regression: $\log\left(\frac{P(Y=1|X)}{1-P(Y=1|X)}\right) = \beta_0 + \beta_i X_{i,t} + \varepsilon_t$ where the dependent variable is a dummy variable Y that has a value of 1 if $BSADF_{r2,t} \geq cv_{r2,t}^{\alpha T}$ (when there is price explosiveness as evidenced by the increase of the BSADF sequence above corresponding critical value) and 0 if $BSADF_{r2,t} \leq cv_{r2,t}^{\alpha T}$; β_0 denotes the constant; $X_{i,t}$ is a set of nine dummy variables, where $i = 1,2\ldots0.9$; each dummy variable implies price explosiveness as shown for the dependent variable, in each of the other remaining nine cryptocurrencies; ε_t represents the error term assumed to be distributed as the logistic distribution

Table 16 BDS residual independence tests for linear regression models described in Eqs. 6, 7, 8, 9, 10, 11 and 12

	$CSAD_{m,t}$ (Eq. 6)	$CSAD_{wb,t}$ (Eq. 7)	$CSAD_{s,t}$ (Eq. 8)	$p_{i,t}$ (Eq. 9)	$w_{i,t}$ (Eq. 10)	Δy_t (Eq. 11)	Δy_t (Eq. 12)
BDS (2,1)	0.3761 (0.2603)	0.4385 (0.3374)	0.4887 (0.3990)	0.2907 (0.2831)	0.0773 (0.4023)	0.8847 (0.5237)	0.9002 (0.6114)
BDS (3,1)	0.4099 (0.3372)	0.5229 (0.3994)	0.5916 (0.4021)	0.3226 (0.3171)	0.0904 (0.5170)	0.9021 (0.7038)	0.9663 (0.8660)
BDS (4,1)	0.6812 (0.5802)	0.7811 (0.6635)	0.8003 (0.6857)	0.3899 (0.3884)	0.1005 (0.7188)	0.9769 (0.8172)	0.9983 (0.9021)

We specify the test statistic as:

$BDS_{m,T}(d) = T^{0.5}\left[C_{m,T}(d) - C_{1,T}(d)^m\right]/\sigma_{m,T}(d)$

where σ represents the sample standard deviation of the data, and $C_{m,T}(d)$ denotes the sample correlation integral given 'embedding dimension', m, and distance, d. The BDS statistic is asymptotically distributed as a standard normal, $BDS_{m,T} \sim N(0, 1)$ when applied to IID series. The BDS $p -$ values are presented in parentheses

Appendix C

(a) Relationship between CSAD and CMR

We adopted the empirical procedure of Chang, Chen and Khorana (2000) to explain both the linear and the non-linear relationship between the cross-sectional absolute deviation of returns (CSAD) and the cryptocurrency market return (CMR):

$$E_t(R_i) = \gamma_0 + \beta_i E_t(CMR - \gamma_0) \tag{21}$$

where E_t represent the expectation in period t; CMR denote the cryptocurrency market return; R_i denote the return of each cryptocurrency; γ_0 shows the zero-beta portfolio return while β_i represent the time-invariant systematic risk measure of the cryptocurrency, $i = 1, ..., N$ and $t = 1, ..., T$. Given that β_m is the systematic risk in the CAPM, we obtain:

$$\beta_m = \frac{1}{N}\sum_{i=1}^{N}\beta_i \tag{22}$$

The absolute value of the deviation (AVD) of cryptocurrency's i expected return in period t can be presented as:

$$AVD_{i,t} = |\beta_i - \beta_m| E_t(CMR - \gamma_0) \tag{23}$$

Therefore, we can compute the expected cross-sectional absolute deviation of cryptocurrency returns (ECSAD) in period t in the following way:

$$ECSAD_t = \frac{1}{N}\sum_{i=1}^{N} AVD_{i,t} = \frac{1}{N}\sum_{i=1}^{N}|\beta_i - \beta_m| E_t(CMR - \gamma_0) \tag{24}$$

Hence, we can estimate the linear relation between dispersion and the time-varying market expected returns as:

$$\frac{\partial ECSAD_t}{\partial E_t(CMR)} = \frac{1}{N}\sum_{i=1}^{N}|\beta_i - \beta_m| > 0, \tag{25}$$

$$\frac{\partial^2 ECSAD_t}{\partial E_t(CMR)^2} = 0, \tag{26}$$

To represent the non-linear relationship between CSAD and CMR, we use $CSAD_t$ and CMR as proxy for the unobservable $ECSAD_t$ and $E_t(CMR)$. There will be a less than proportional increase in the CSAD estimate when cryptocurrency market participants are more likely to herd during periods of significant price fluctuations. To capture the likelihood of asymmetric degree of herding behaviour in the up-against-the-down-cryptocurrency market, we perform the following econometric specification:

$$CSAD_t^{UP} = \alpha + \gamma_1^{UP}\left|CMR^{UP}\right| + \gamma_2^{UP}\left(CMR^{UP}\right) + \varepsilon_t \tag{27}$$

$$CSAD_t^{DOWN} = \alpha + \gamma_1^{DOWN}\left|CMR^{DOWN}\right| + \gamma_2^{DOWN}\left(CMR^{DOWN}\right) + \varepsilon_t \tag{28}$$

A non-linear relation between CSAD and CMR would occur when cryptocurrency market participants experience herding towards indicators such as the average consensus of all market constituents during intervals of large price fluctuations.

(b) Relationship between CMR and $r_{m,t}$

Based on Cochrane (2005) we explain the relationship between cryptocurrency market return (CMR) and the cross-sectional average market return ($r_{m,t}$) in the following way. While *CMR* describes how average returns change over time, $r_{m,t}$ measure how average returns change across different cryptocurrencies. In simple terms, examining the cross section of cruptocurrency returns, researchers want to answer the question why cryptocurrency A generates higher or lower returns than cryptocurrency B across section of many cryptocurrencies at one point in time. Cochrane (2005) argues that the CAPM is effectively a model that explains the cross-section of stock returns with only one factor, the systematic risk of a stock. Considering that the CAPM is empirically not successful in explaining the stock returns thoroughly, there are other models, such as the Fama-French 3 factor model.

The existing literature explains the direct relation between market return and cross-sectional market return, as the former can explain and influence the latter. For example, Long, Zaremba, Demir, Szczygielski and Vasenin (2020) deploy cross-sectional regressions to investigate daily returns on 151 cryptocurrencies between 2016 and 2019 and observe that average past same-weekday returns positively predict future performance in the cross-section. Moreover, the authors report that cryptocurrencies with high same-day returns in the past outperform those with low same-day returns. In terms of the stock market, long-term past returns (DeBondt & Thaler, 1985) and short-term past returns (Jegadeesh & Titman, 1993) can explain the cross-sectional variation in stock returns.

References

Agosto, A., & Cafferata, A. (2020). Financial bubbles: A study of co− explosivity in the cryptocurrency market. *Risks, 8*(2), 1–14.

Ait−Sahalia, Y. and Seglam, M. (2017). High frequency market making: Implications for liquidity. Working paper. Princeton University.

Alexander, C., & Dakos, M. (2019). A critical investigation of cryptocurrency data and analysis. *Quantitative Finance, 20*(2), 173–188.

Alomari, M., & Al Rababa'a, A.R., El− Nader, G., Alkhataybeh, A., Ur Rehman, M. (2021). Examining the effects of news and media sentiments on volatility and correlation: Evidence from the UK. *The Quarterly Review of Economics and Finance, 82*, 280–297.

Anderson, L. R., & Holt, C. (1997). Information cascades in the laboratory. *American Economic Review, 87*(5), 847–862.

Anshuman, V. R., & Subrahmanyam, A. (1999). Price limits, information acquisition and bid−Ask spreads: Theory and evidence. *Economic Notes, 28*(1), 91–118.

Antonakakis, N., Chatziantoniou, I., & Gabauer,. (2019). Cryptocurrency market contagion: Market uncertainty, market complexity, and dynamic portfolios. *Journal of International Financial Markets Institutions and Money, 61*, 37–51.

Banerjee, A. V. (1992). A simple model of herd behaviour. *Quarterly Journal of Economics, 107*(3), 797–817.

Bhosale, J., & Mavale, S. (2018). Volatility of select crypto-currencies: A comparison of Bitcoin, Ethereum and Litecoin. *Annual Research Journal of SCMS, Pune, 6*, 132–141.

Bianchetti, M., Ricci, C. and Scaringi, M. (2018). Are Cryptocurrencies Real Financial Bubbles? Evidence from Quantitative Analyses. Working paper. Intesa Sanpaolo − Financial and Market Risk Management; University of Bologna.

Boulton, T. J., & Braga− Alves, M.V. and Kulchania, M. (2014). The flash crash: An examination of shareholder wealth and market quality. *Journal of Financial Intermediation, 23*, 140–156.

Bouri, E., Gupta, R., & Roubaud, D. (2019). Herding behaviour in cryptocurrencies. *Finance Research Letters, 29*, 216–221.

Brauneis, A., Mestel, R., Riordan, R., & Theissen, E. (2021). How to measure the liquidity of cryptocurrency markets? *Journal of Banking & Finance, 124*, 106041.

Brock, W., Dechert, W. D., Scheinkman, J., & LeBaron, B. (1996). A test for independence based on the correlation dimension. *Econometric Reviews, 15*, 197–235.

Buyrukoğlu,S. (2021). Promising cryptocurrency analysis using deep learning. In: *2021 5th International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*.

Cagli, E. (2019). Explosive behavior in the prices of bitcoin and altcoins. *Finance Research Letters, 29*, 398–403.

Cerchiello, P., & Nicola, G. (2018). Assessing news contagion in finance. *Econometrics, 6*(1), 1–19.

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

Chang, E. C., Chen, J. W., & Khorama, A. (2000). An examination of herd behavior in equity markets: An international perspective. *Journal of Banking and Finance, 24*, 1651–1679.

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

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

Chiang, T. C., & Zheng, D. (2010). An empirical analysis of herd behavior in global stock markets. *Journal of Banking and Finance, 34*(8), 1911–1921.

Cochrane, J. (2005). *Asset Pricing* (Revised). Princeton University Press.

CoinSwitch. (2018d). What is Lisk (LSK)? Future of LSK Cryptocurrency and know how to buy LSK [online]. Available from https://coinswitch.co/info/lisk/what−is−lisk.

CoinSwitch. (2018e). What is Neo (NEO)? Future of NEO Cryptocurrency and know how to buy NEO [online]. Available from https://coinswitch.co/info/neo/what−i−neo.

CoinSwitch. (2018f). What is Nem (Xem) (XEM)? Future of XEM Cryptocurrency and know how to buy XEM [online]. Available from https://coinswitch.co/info/nem/what-is−nem.

CoinSwitch. (2018a). Possible reasons for today's cryptocurrency market crash [online]. Available from https://coinswitch.co/news/possible−reasons−or−today−cryptocurrency−market−crash−october−11−2018a.

CoinSwitch.(2018b). What is Bitcoincash (BCH)? Future of BCH Cryptocurrency and know how to buy BCH [online]. Available from https://coinswitch.co/info/bitcoin−cash/what−is−bitcoin−cash.

CoinSwitch.(2018c). What is EOS? Future of EOS Cryptocurrency and know how to buy EOS [online]. Available from https://coinswitch.co/info/eos/what−is−eos.

Connolly, R. A. (1989). An examination of the robustness of the weekend effect. *Journal of Financial and Quantitative Analysis, 24*, 133–169.

Corber, S., Lucey, B., & Yarovaya, L. (2018). Datestamping the Bitcoin and Ethereum bubbles. *Finance Research Letters, 26*, 81–88.

Cretarola, A., & Figà- Talamanca, G. (2020). Bubble regime identification in an attention−Based model for bitcoin and ethereum price dynamics. *Economics Letters, 191*, 108831.

DeBondt, W., & Thaler, R. (1985). Does the stock market overreact? *Journal of Finance, 40*, 793–905.

Demsetz, H. (1968). The cost of transacting. *Quarterly Journal of Economics, 82*(1), 33–53.

Diebold, F., & X., and Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting, 28*, 57–66.

DiGeorgia, J. (2018). The 2018 cryptocurrency crash is proving to be catastrophic [online]. https://wallstreetrebel.com/wsr/cryptocurrency/the_2018_cryptocurrency_crash_is_proving_to_be_catastrophic/2018-09-13-14-25-32.html. Accessed on 01/09/2020.

Donier, J., & Bouchaud J− P,. (2015). Why Do markets crash? Bitcoin data offers unprecedented insights. *PLoS ONE, 10*(10), e0139356. https://doi.org/10.1371/journal.pone.0139356

Enoksen, F. A., Landsnes, C. J., Lučivjanská, K., & Molnár, P. (2020). Understanding risk of bubbles in cryptocurrencies. *Journal of Economic Behavior and Organization, 176*, 129–144.

Eom, Y. (2020). Kimchi premium and speculative trading in bitcoin. *Finance Research Letters*. https://doi.org/10.1016/j.frl.2020.101505

Fantazzini, D., Dalla Valle, L., & Giudici, P. (2008). Copulae and operational risks. *International Journal of Risk Assessment and Management, 9*(3), 238–257.

Fruehwirt, W., Hochfilzer, L., Weydemann, L., & Roberts, S. (2020). Cumulation, crash, coherency: A cryptocurrency bubble wavelet analysis. *Finance Research Letters*. https://doi.org/10.1016/j.frl.2020.101668

Fry, J., & Cheah, E− T. (2016). Negative bubbles and shocks in cryptocurrency markets. *International Review of Financial Analysis, 47*, 343–352.

Geuder, J., Kinateder, H., & Wagner, N. F. (2019). Cryptocurrencies as financial bubbles: The case of Bitcoin. *Finance Research Letters, 31*, 179–184.

Giudici, P., & Bilotta, A. (2004). Modelling operational losses: A bayesian approach. *Quality and Reliability Engineering International, 20*, 407–417.

Giudici, P., & Pagnottoni, P. (2019). High frequency price change spillovers in bitcoin markets. *Risks, 7*(4), 111.
Giudici, P., & Polinesi, G. (2021). Crypto price discovery through correlation networks. *Annals of Operations Research, 299*, 443–457.
Giudici, P., & Raffinetti, E. (2021). Shapley-Lorenz eXplainable Artificial Intelligence. *Expert Systems with Applications, 167*, 114104.
Greenwald, B. C., & Stein, J. C. (1991). Transactional risk, market crashes, and the role of circuit breakers. *Journal of Business, 64*(4), 443–462.
Gronwald, M. (2019). Is Bitcoin a commodity? On price jumps, demand shocks, and certainty of supply. *Journal of International Money and Finance, 97*, 86–92.
Hendershott, T., & Seasholes, M. (2007). Market maker inventories and stock prices. *American Economic Review, 97*, 210–214.
Hitam, N. A., & Ismail, A. R. (2018). Comparative performance of machine learning algorithms for cryptocurrency forecasting. *Indonesian Journal of Electrical Engineering and Computer Science, 11*(3), 1121–1128.
Hong, S. (2021). Cryptocurrency automatic trading research by using Facebook deep learning algorithm. *Journal of Digital Convergence, 19*(11), 359–364.
Huang, J., & Wang, J. (2009). Liquidity and market crashes. *Review of Financial Studies, 22*, 2607–2643.
Huang, J., & Wang, J. (2010). Market liquidity, asset prices, and welfare. *Journal of Financial Economics, 95*, 107–127.
Jegadeesh, N., & Titman, S. (1993). Returns to buying winners and selling losers: Implications for stock market efficiency. *Journal of Finance, 48*, 65–91.
Ji, Q., Bouri, E., Lau, C., & K, M., and Roubaud, D. (2019). Dynamic connectedness and integration in cryptocurrency markets. *International Review of Financial Analysis, 63*, 257–272.
Kalyvas, A., Papakyriakou, P., Sakkas, A., & Urquhart, A. (2020). What drives Bitcoin's price crash risk? *Economics Letters, 191*, 108777.
King, T., & Koutmos, D. (2021). Herding and feedback trading in cryptocurrency markets. *Annals of Operations Research, 300*, 79–96. https://doi.org/10.1007/s10479−020−03874−4
Kirilenko, A., Kyle, A., Samadi, M., & Tuzun, T. (2017). The flash crash: High−frequency trading in an electronic market. *Journal of Finance LXXII, 3*, 967–998.
Kočenda,E. (2010). A Test for Iid Residuals Based on Integrating Over the Correlation Integral. *CERGE−EI Working Paper Series No. 101.*
Kodres, L. E., & O'Brien, D. P. (1994). The existence of pareto−Superior price limits. *American Economic Review, 84*(4), 919–932.
Koker, T., & E. and Koutmos, D. (2020). Cryptocurrency trading using machine learning. *Journal of Risk and Financial Management, 13*(8), 178.
Kyriazis, N., Papadamou, S., & Corbet, S. (2020). A systematic review of the bubble dynamics of cryptocurrency prices. *Research in International Business and Finance, 54*, 101254.
Lauterbach, B., & Ben−Zion U,. (1993). Stock market crashes and the performance of circuit breakers: Empirical evidence. *Journal of Finance, 48*(5), 1909–1925.
Leclair, E. M. (2018). Herding in the cryptocurrency market [online]. https://www.researchgate.net/publication/324833550_Herding_in_the_cryptocurrency_market
Lee, C. (1993). Market integration and price execution for NYSE−listed securities. *Journal of Finance, 48*(3), 1009–1038.
Liashenko, O., Kravets, T., and Repetskyi, Y. (2021) Neural Networks in Application to Cryptocurrency Exchange Modeling. IT&I−2020 Information Technology and Interactions.
Liew, J., & K−S., Li, R.Z., Budavári, T., and Sharma, A. (2019). Cryptocurrency Investing Examined. *The Journal of British Blockchain Association, 2*(2), 1–12.
Lindley, D. V. (1957). A statistical paradox. *Biometrika, 44*, 187–192.
Long, H., Zaremba, A., Demir, E., Szczygielski, J. J., & Vasenin, M. (2020). Seasonality in the cross−section of cryptocurrency returns. *Finance Research Letters, 35*, 101566.
Lucarelli, G. and Borrotti, M. (2019). A deep reinforcement learning approach for automated cryptocurrency trading. Artificial intelligence applications and innovations. In: *15th IFIP WG 12.5 International Conference, AIAI 2019 Hersonissos, Crete, Greece, May 24–26, 2019 Proceedings*.
MacDonell, A. (2014). Popping the bitcoin bubble: An application of log−periodic power law modeling to digital currency. University of Notre Dame. Working Paper.
McMillan, D. G. (2003). Non−linear predictability of UK stock market returns. *Oxford Bulletin of Economics and Statistics, 65*(5), 531–680.
Meade, N. (2002). A comparison of the accuracy of short−term foreign exchange forecasting methods. *International Journal of Forecasting, 18*, 67–83.

Meyer, D. (2018). Bitcoin bloodbath: News from Goldman Sachs is behind today's plunging cryptocurrency prices [online]. Available from http://fortune.com/2018/09/06/bitcoin−crash−goldman−sachs−crypto currencies/. Accessed on 10/02/2022.
Nguyen, L. H., Chevapatrakul, T., & Yao, K. (2020). Investigating tail−risk dependence in the cryptocurrency markets: A LASSO quantile regression approach. *Journal of Empirical Finance, 58*, 333–355.
Omrane, B. W., Guesmi, K., Qianru, Q., & Saadi, S. (2021). The high−frequency impact of macroeconomic news on jumps and co−jumps in the cryptocurrency markets. *Annals of Operations Research*. https://doi.org/10.1007/s10479−021−04353−0
Poyser, O. (2018). *Herding behaviour in cryptocurrency markets*. USA: Cornell University Library.
SEC. (2001). *Report of the advisory committee on market information: A blueprint for responsible change*. Report, USA: Securities and Exchange Commission, Washington, D.C.
Shroeder, S. (2018). Crypto market is crashing hard, here's why [online]. Available from https://mashable.com/article/crypto−market−crash−august−2018/?europe=true#vonlMSN07Pq4
Shu, M., & Zhu, W. (2020). Real−time prediction of Bitcoin bubble crashes. *Physica A: Statistical Mechanics and its Applications, 548*, 124477.
Sun, J., Zhou, Y., and Lin, J. (2019). Using machine learning for cryptocurrency trading. In: *2019 IEEE International Conference on Industrial Cyber Physical Systems (ICPS)*.
Szakmary, A. C., & Keifer, D. B. (2004). The disappearing January/Turn of the year effect: Evidence from stock index futures and cash markets. *The Journal of Futures Markets, 24*(8), 755–784.
Vidal Tomás, D., Ibánes, A. M., & Farinós, J. E. (2018). Herding in the cryptocurrency market: CSSD and CSAD approaches. *Finance Research Letters*. https://doi.org/10.1016/j.frl.2018.09.008
Westerhoff, F. (2003). Speculative markets and the effectiveness of price limits. *Journal of Economic Dynamics and Control, 28*(3), 493–508.
Wheatley, S., Sornette, D., Huber, T., Reppen, M., & Gantner, R. N. (2018). Are bitcoin bubbles predictable? Combining a Generalized Metcalfe's Law and the LPPLS Model (2018), Swiss Finance Institute Research Paper (18–22).
White, H. (1980). A heteroscedasticity−consistent covariance matrix estimator and a direct test for heteroscedasticity. *Econometrica, 48*, 817–838.
Xiong, J., Liu, Q., & Zhao, L. (2019). A new method to verify bitcoin bubbles: based on the production cost. *North American Journal of Economics and Finance, 51*, 101095.
Yao, J., Ma, C., & He, W. P. (2014). Investor herding behaviour of Chinese stock market. *International Review of Economics and Finance, 29*, 12–29.
Yaya, O. S., Ogbonna, A. E., & Olubusoye, O. (2019). How persistent and dynamic inter−dependent are pricing of Bitcoin to other cryptocurrencies before and after 2017/18 crash? *Physica A: Statistical Mechanics and its Applications, 531*, 121732.
Zhang, W., Li, Y., Xiong, X., & Wang, P. (2021). Downside risk and the cross−section of cryptocurrency returns. *Journal of Banking & Finance, 133*, 106246.