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Abstract

Bitcoin futures were introduced in December 2017 and this was seen by some as a sign of the most popular cryptocurrency finally being accepted by the financial community. In this paper, we examine the impact of the introduction of Bitcoin futures on the Bitcoin spot market in terms of five characteristics - returns, volatility, skewness, kurtosis and liquidity, using a Bayesian diffusion-regression (state-space) structural time-series model. Our results indicate that the introduction of bitcoin futures potentially exerted a downward impact on the USD bitcoin spot market return and skewness and an upward one on volatility, kurtosis and liquidity, which became higher after futures were introduced. Therefore, our paper offers important insights for investors and regulators, while providing some guidance as to the potential impact of futures markets on other cryptocurrencies.

Keywords: Bitcoin Futures; Returns; Volatility; Liquidity

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1. Introduction

The introduction of Bitcoin futures in early December 2017 marked one of the most crucial landmarks in the development of cryptocurrency markets. With the introduction of Bitcoin futures on the Chicago Board Options Exchange (CBOE) and the Chicago Mercantile Exchange (CME), investors could now speculate on falling prices ("go short") and interestingly, according to Robert Shiller, it was exactly this lack of being able to go short which was responsible for the Bitcoin pricing bubble in 2017 (Shiller 2017). The impact of the introduction of futures markets has had a profound effect on the Bitcoin market, with some papers documenting a significant increase in the spot volatility of Bitcoin (Corbet et al. 2018; Kim et al. 2020), a crash in Bitcoin price after the introduction of futures (Ruozhou et al. 2020), an impact on the market efficiency of Bitcoin (Shynkevich 2020), while some papers find that the price discovery of Bitcoin now originates in the future market rather than the spot market (Kapar and Olmo 2019; Fassas et al. 2020). Therefore the impact of a futures market has had a huge effect on the Bitcoin market.

This study attempts to shed light on the causal impact of the introduction of Bitcoin futures in December 2017 on five properties of the Bitcoin spot market, namely returns, volatility, skewness, kurtosis and liquidity. Specifically, we attempt to answer the question - what could the Bitcoin market look like if the Bitcoin futures had never been introduced? To answer this question, we implement a diffusion-regression (state-space) structural time-series model (Brodersen et al., 2015) that helps us predict the Bitcoin market response to the introduction of Bitcoin futures. This is an important topic to study since the listing of Bitcoin futures on the main futures exchanges was a landmark event for Bitcoin since it brought Bitcoin trading to a regulated market for the first time and therefore opened up Bitcoin trading to a larger audience. Our paper examines what would have happened to the main variables of Bitcoin if Bitcoin futures had not been introduced.

Bitcoin, proposed by Satoshi Nakamoto in 2008, was the first digital currency to operate through a peer-to-peer network without reliance on a central authority. It has received a lot of attention from the media, governments, regulators and investors alike, who have been attracted by its innovative features and huge price appreciation. However, this price appreciation has come with large volatility and uncertainty regarding the future price path of this popular cryptocurrency. The Bitcoin literature so far has mainly focused on the inefficiency of Bitcoin (Urquhart 2016; Bariviera 2017; Tiwari et al 2018; Wei 2018; Sensoy 2019), its hedging and diversification benefits (Bouri et al 2017; Corbet et al 2019a; Urquhart and Zhang 2018; Borri 2019), potential for returns from investing in Bitcoin (Brière et al 2015; Hudson and Urquhart 2019; Kajtazi and Moro 2019; Platanakis and Urquhart 2019) as well as the volatility dynamics of Bitcoin (Katsiampa 2017; Chaim and Laurini 2018; Catania et al 2019; Matkovskyy 2019; Katsiampa 2019).[1]

One the key developments of Bitcoin was the introduction of futures trading which was seen as a sign that the financial system was beginning to accept Bitcoin as a tradeable speculative asset.[2] The introduction was also important for Bitcoin traders as for the first time, they were able to easily hedge their spot positions. CBOE Futures (XBT) and CME Futures (BTC) were launched on the 10th and 18th of December 2017, respectively, and this event was met with a mixed market reaction. Proponents argued that the introduction of the futures market would mean a move towards market efficiency and better liquidity while opponents blamed it for the sharp drop in Bitcoin prices. Academic thought in this regard remains mixed. For instance, Liu et al (2019) show that the launch of Bitcoin futures caused the crash of Bitcoin in 2018. On the other hand, Hattori and Ishida (2019) document that Bitcoin futures trading had a negative effect on Bitcoin prices only in the first 19 minutes, and not over the longer term. In a similar vein, Hale et al. (2018) show that the post-launch drop in Bitcoin prices is consistent with investor behaviour in traditional asset markets when futures are introduced for the first time (Fostel and Geanakoplos, 2012).

Several studies have documented positive effects of futures trading on the overall Bitcoin market, such as an increase in Bitcoin market efficiency (Köchling et al. 2018; Matkovskyy and Jalan 2019). Ruozhou et al. (2020) document that while the launch of Bitcoin futures caused a

[1] For a systematic review of the literature on Bitcoin, see Corbet et al (2019).

[2] Through an examination of transaction data, Baur et al (2018) show that Bitcoin is mainly used as a speculative investment by investors and not as an alternative currency or medium of exchange.

significant decrease in short-term Bitcoin prices, other cryptocurrencies remained largely unaffected. Kim et al (2019) document greater Bitcoin spot market stability post-launch of Bitcoin futures while Kapar and Olmo (2019) show that Bitcoin futures dominate the price discovery process while both the futures and spot prices are driven by a common factor which is a combination of the futures and spot price. Using the information share methodology of Hasbrouck (1995), Baur and Dimpfl (2019) show that the Bitcoin spot price leads future prices in terms of price discovery, which is attributed to higher trading volume and longer trading hours of the spot market compared to the US-based futures markets.[3] In a recent paper, Alexander et al. (2019) document that derivatives on the unregulated BitMEX exchange lead prices on major Bitcoin exchanges and are effective hedges against spot price volatility.

In general, derivative markets offer several advantages such as lower transaction costs, higher liquidity and ease of short selling (Chance and Brooks, 2013). However, in the literature, there are contradictory findings regarding the impact of the introduction of futures trading on the spot market. For instance, some studies find that the introduction of derivatives has a destabilizing effect on the respective spot market (Cox, 1976; Cagan, 1981; Hart and Kreps, 1986; Stein, 1987). For example, Jegadeesh and Subrahmanyam (1993) suggest that after introducing futures for the S&P500 index, the average spread of its stocks increased significantly. Similarly for volatility, Harris (1989) document that for the S&P500, volatility increased after the introduction of derivatives in 1983, which has been supported in other international markets (for instance Antoniou and Holmes 1995; Pok and Poshakwale 2004; Ryoo and Smith 2004; Zhong, Darraf and Otero 2004; Xie and Mo 2014; Xie and Huang 2014; Kutan et al. 2018) and commodity markets (Yang et al. 2005; Gupta and Varma, 2016; etc).

An alternative finding in the literature is that the introduction of a futures markets stabilizes the spot market by lowering the volatility of the market (for instance Powers 1970; Kyle 1985; Antoniou et al 1998). Gulen and Mayhew (2000) study stock market volatility before and after the

[3] This finding is also supported by a previous study by Corbet et al (2018).

launch of equity-index futures trading in twenty-five countries and find that for 16 countries out of 25, the introduction of futures led to decreased volatility in the underlying stock markets. Antoniou, Koutmos and Pericli (2005) demonstrate that futures markets help stabilize the underlying spot markets. Chen, Han, Li, and Wu (2013) document that the launch of index futures trading significantly reduces the volatility in the Chinese stock market. Lee et al. (2014) document lower volatility in the European real-estate market following the launch of the real-estate futures contracts in 2007. Bohl, Diesteldorf, and Siklos (2015) document that Chinese index futures decrease spot market volatility in mainland China with Chinese index futures traded in Singapore and Hong Kong. Nevertheless, there is some evidence that the introduction of futures markets has no significant effect on the spot market (Freris, 1990; Schwert, 1990; Antoniou and Foster, 1992; Bacha and Vila, 1994; Darrat and Rahman, 1995; Fortenbery and Zapata, 1997; Jochum and Kodres, 1998; Lee and Tong, 1998; Bohl and Stephan, 2013).

Given the conflicting views of the impact of the launch of futures markets, we examine the causal impact on a number of important facets of the Bitcoin market. The causal impact of an intervention is the difference between the observed time series of the response (Bitcoin returns, volatility, skewness, kurtosis and liquidity) and the unobserved series that would have been observed had the intervention not happened (Brodersen et al. 2015). This causal impact is studied using the methodology outlined in Brodersen et al. (2015)[4] that uses a Bayesian approach to infer the temporal evolution of activity and incremental impact.

In our empirical study, we use Bitcoin return, variance, volatility, skewness, kurtosis and liquidity as the treatment variables, which on the basis of findings related to other financial markets (Cox, 1976; Cagan, 1981; Pindyck 1983; Hart and Kreps, 1986; French et al. 1987; Ross 1989; Nelson 1990; Gulen and Maydew 2000; Mitton and Vorkink, 2007; Barberis and Huang, 2008 etc.) could potentially be affected by the introduction of Bitcoin futures. Other cryptocurrencies, namely

[4] Brodersen et al. (2015) offer the method to construct the "counterfactual" that is similar conceptually to synthetic diff-in-diff methods (e.g. Abadie and Gardeazabal 2003; Abadie 2005; and Abadie, Diamond and Hainmueller 2010). It is implemented in CausalImpact R package.

Ethereum and Litecoin, that are not directly affected by the intervention, i.e., the launch of Bitcoin futures, but remain correlated with our variables of interest (Köchling et al. 2018) are used as the control time series.

Our results contribute to existing literature by quantifying the effect of the introduction of Bitcoin futures on bitcoin spot market return, volatility, realized kurtosis, realized skewness and liquidity. Our simulation shows that if bitcoin futures had never been introduced, the USD bitcoin spot market return would be higher, volatility and kurtosis lower, skewness higher and finally, market liquidity lower.

Thus, our findings show that the introduction of bitcoin futures had a significant negative effect on return and a significant positive impact on spot market volatility. The negative relationship observed between bitcoin volatility and return can be due to greater risks (Chung and Chuwonganant 2018) and is consistent with expected risk premium and volatility (French et al. 1987). In terms of skewness, the introduction of bitcoin futures decreases the degree of asymmetry of the return distribution around its mean. Following Lien and Wang (2012), this could be interpreted as a potential increase in demand for hedging following the introduction of bitcoin futures. In addition, our results support the finding of Bris et al (2007) who postulate that returns in markets in which short-selling is not practiced, typically exhibit significantly less negative skewness. The launch of Bitcoin futures ended up making the bitcoin spot market not only more volatile but also more vulnerable to extreme return values. This can be witnessed from sharp increases in realized kurtosis values of the USD bitcoin spot market. This could potentially deter risk-averse investors from participating in the market after the launch of futures. In short, in terms of all three aspects of volatility, skewness and kurtosis, the launch of bitcoin futures seems to have destabilized the USD bitcoin spot market. We observe however, that the launch of futures resulted in a tiny positive effect in bitcoin spot market liquidity, but unfortunately, this effect is not strong enough to stabilize this already highly-volatile market.

The overall picture seems to suggest that the introduction of bitcoin futures had a significantly positive impact on spot volatility and a significantly negative impact on Bitcoin returns. Even when this may sound surprising, this is in line with the findings of Ang et al. (2006) who find that investors typically expect lower returns from stocks with overall high levels of volatility. The results support the hypothesis that the introduction of bitcoin futures, in general, contributed to destabilizing the USD bitcoin spot market (Cox, 1976; Cagan, 1981; Hart and Kreps, 1986; Stein, 1987), with volatility as the main channel for destabilization.

The rest of this paper is organized as follows. Section 2 introduces the data, the variables of interest and the methodology while Section 3 presents the empirical results. Section 4 summarizes our paper and provides conclusions.

2. Data, variables of interest and methodology

2.1. Data

We collect hourly Bitcoin price data from the Bitstamp exchange and that for Ethereum and Litecoin, from Kraken, over the period 1st July 2017 to 10th October 2019. Our sample period is chosen due to data availability of Ethereum and Litecoin. The Bitstamp, one of the longest running exchanges, is highly liquid and also the exchange used by Datastream (Platanakis and Urquhart 2019). On the other hand, LTC and ETH are not available on Bitstamp from the same day as Bitcoin. Given the need to have the longest possible time series before the introduction of futures for an efficient application of the Brodersen (2015) methodology, we take closing price and volume data for LTC and ETH from Kraken, which provides a much longer time series of observations.[5]

Even when the three cryptocurrencies are interconnected (Koutmos 2018; Antonakakis et al. 2019; and Ji et al. 2019; Smales 2020), the literature suggests that Ethereum and Litecoin remained unaffected by the bitcoin futures launch. Indeed, cryptocurrencies' connectedness is a

[5] Kraken data has been extensively used in published cryptocurrency research. For instance, Matkovskyy and Jalan (2020), Matkovskyy (2019) who use closing price data from this exchange. Alexander and Dakos (2020) conclude that data from Kraken, as used in Matkovskyy (2019) is accurate.

well-documented phenomenon. For instance, Sifat et al. (2019) document the presence of bi-directional causality between bitcoin and Ethereum. Moratis (2020) provides support to the evidence that connectedness among cryptocurrencies is not explicitly determined by their size. Yi et al. (2018) analyse volatility connectedness of 8 cryptocurrencies – bitcoin, Ripple, Litecoin, Peercoin, Namecoin, Feathercoin, Novacoin and Terracoin using the Spillover Index approach (Diebold and Yilmaz, 2009). They find that overall connectedness increased after 2016 and that the bitcoin is an important transmitter of connectedness, though not the dominant one.

Ji et al. (2019) examine return connectedness for 6 large cryptos – Bitcoin, Ethereum, Ripple, Litecoin, Stellar and Dash, using Diebold and Yilmaz (2012, 2016) measures and show that shocks in Bitcoin returns, followed by Litecoin have the greatest impact on other cryptocurrencies. They present evidence that cryptocurrency connectedness is not necessarily related to its market size. Bouri et al. (2020) study cryptocurrency connectedness using return jumps on a sample of 12 cryptocurrencies, including Ethereum and Litecoin. They document that the presence of a jump in one currency increases the probability of inducing a jump in another, showing connectedness of bitcoin and Ethereum. Similarly, Gonzalez et al. (2020) in their study of both long- and short-run interdependencies between returns of Bitcoin and Ethereum, XRP, Bitcoin Cash, Tether, Bitcoin SV, Litecoin, EOS, Binance coin, and Tezos by means of a NARDL approach, document evidence of connectedness, i.e., the presence of short-run and long-run responses of cryptocurrencies' returns to changes in bitcoin return for all frequencies. Using wavelet coherence analysis and 5-minute data, Fruehwirt et al. (2020) show significant co-movement and interdependence among the cryptocurrencies. On the other hand, given that the only underlying asset of Bitcoin futures is bitcoin, there is evidence that the other cryptocurrencies are insulated to some extent to the bitcoin futures launch (Ruozhou et al. 2020). We also find support for our claim in Shynkevich (2020) who documents no evidence of improvement of market efficiency of Ethereum following the start of trading in bitcoin futures.

A volatility signature is applied to test for overall volatility for different frequencies of Bitcoin close prices. This is in line with Andersen et al. (1999) who address the issue of selection of an appropriate sampling frequency in the light of high frequency data. They argue that the 'ideal' frequency for calculation of realized volatility of asset returns must be selected in a manner that minimises both microstructural bias and sampling error. This is made possible with the help of a volatility signature plot that represents average realized volatility against various sampling intervals. The ideal frequency to be selected is one where one observes a relative stabilization of overall volatility.

Since their introduction, volatility signature plots have been employed across various academic studies in finance to address data frequency issues (see for instance, Corsi et al. 2008, Degiannakis and Floros, 2013 and for cryptocurrencies in particular by Akyildirim et al., 2020 and Shen et al. 2020.).

The volatility signatures are depicted in Figure 1 and shows that the volatility of Bitcoin levels off around the 60-minute frequency. Specifically during the first 10 minutes, bitcoin volatility decreased from 2.6 to 0.2 (90% decrease) while between 11-60 minutes, it decreased from 0.2 to 0.04 (78% decrease) and then after that, volatility dropped from 0.04 to 0.02 which indicates the levelling off volatility. Therefore, based on these volatility signature results, one can conclude that the 60 minutes' frequency is best suited for our tests from the point of view of noise minimization.

2.2. Variables of Interest

The variables of interest in this paper are the daily Bitcoin return, volatility, skewness, kurtosis and liquidity that are considered to be of significant interest to researchers, market regulators, investors (Chung and Chuwonganant 2018).

We calculate log returns as:

$$r_t = (InP_t - InP_{t-1}) \times 100 \quad (1)$$

Where r_t is the daily return on day t and P_t and P_{t-1} are the prices at day t and day t-1.

Realized variance (RV), is defined any given day t as the sum of the squared intraday returns $r_{t,j}$ at a given sampling frequency $1/M$:

$$RV_{t,M} = \sum_{j=1}^{M} r_{t,j}^2 \quad (2)$$

where M is the number of intervals in the trading day. We choose hourly data because for any higher frequency, we observe lack of liquidity.

Realized volatility is calculated by applying the median realized volatility, medRV, of Andersen et al. (2012). This approach has better efficiency properties than other formalizations for volatility and displays better finite-sample robustness to jumps and small returns. It is based on the theoretical development of Andersen and Bollerslev (1998) and Merton (1980) and was empirically supported and further developed as a less noisy, unbiased and consistent estimator (Anderson et al, 2003, 2007, 2010; 2011a,b; 2012; Engle and Gallo, 2006; Corsi, Pirino, and Renò, 2010; Liu et al., 2017; Ma et al., 2017). Chen et al. (2011) show that this approach generally outperforms stochastic volatility models as well as the generalized autoregressive conditional heteroscedastic models (Santos and Ziegelmann, 2014; Vortelinos, 2017 etc.). Also, this approach can effectively address possible abrupt jumps in volatility."

It is calculated as following:

$$medRV_t = \frac{\pi}{6 - 4\sqrt{3} + \pi}\left(\frac{M}{M-2}\right)\sum_{i=2}^{M-1} med(|r_{t,i-1}|, |r_{t,i}|, |r_{t,i+1}|)^2 \quad (3)$$

where M is the number of intervals in one day and r_t is the return at time *t*. This estimate has a number of advantages comparatively to simple realized variance calculation, that is biased, inconsistent, and not robust to jumps. Also, we prefer the median realized volatility measure instead of the bipower variation measure because the latter is biased in empirical applications as the sampling frequency is not high enough to eliminate the influence of jumps, and the sample may include a number of zero returns. The MedRV allows the impact of jumps to completely vanish except in the case of two consecutive jumps and it is robust to the occurrence of zero returns.

For the purpose of checking robustness we also calculated the time-varying GARCH models (tGARCH, GARCH-in-mean etc.) volatility that are a standard instrument in volatility estimation and the time dependent variance as the stochastic volatility with student-t errors and leverage, that provide more sophisticated framework for volatility estimates.

The time dependent variance as the stochastic volatility with student-t errors and leverage models proposed and further developed by Jacquier et al. (2004), Omori et al. (2007), Nakajima and Omori (2009) among others. This type of model is based on the seminal work of Taylor (1982), which addresses heteroskedasticity using a non-linear latent state space model, later termed the stochastic volatility (SV) model. In SV models, the volatility process evolves in a stochastic manner and offers various advantages over GARCH models (Kim, Shephard, and Chib 1998; Nakajima 2012).

The univariate stochastic volatility model with leverage, heavy tails and correlated jumps is specified as follows (Harvey and Shephard 1996; Omori, Chib, Shephard, and Nakajima 2007; Nakajima and Omori 2012):

$$y_t = x_t\beta + \exp(h_t/2)\varepsilon_t,$$

$$h_{t+1} = \mu + \varphi(h_t - \mu) + \sigma\eta_t,$$

$$\varepsilon_t \sim t_v(0,1),$$

$$\eta_t \sim \mathcal{N}(0,1),$$

Where $y = (y_1, \dots, y_n)^T$ is a vector of observations, μ is the level, φ is the persistence, and σ is the standard deviation of the log-variance. The log variance process $h = (h_1, \dots, h_n)^T$ is initialized by $h_0 \sim \mathcal{N}\left(\mu, \frac{\sigma^2}{1-\varphi^2}\right)$, $X = (x_1, \dots, x_n)^T$ is an *n* x *K* matrix with the vectors of *K* regressors at time *t* in its *t*-th row, the K regression coefficients are collected in β, t_v(a, b) is the Student's t distribution with *v* degrees of freedom, mean *a,* and variance *b,* the correlation matrix of (ε_t, η_t) is defined as $\Sigma^p = \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}$.

Bayesian inference using an MCMC sampling scheme is applied to derive the estimates. We also measure realised skewness and kurtosis as in Amaya et al. (2011):

$$RSkewness_t = \frac{\sqrt{N}\sum_{i=1}^{N}(r_{t,i})^3}{RV_t^{3/2}} \tag{4}$$

$$RKurtosis_t = \frac{\sqrt{N}\sum_{i=1}^{N}(r_{t,i})^4}{RV_t^{2}} \tag{5}$$

where RV is realized variance. These two measures enable us to study the normality of returns and determine the negative or positive skewness as well as the excess kurtosis of Bitcoin returns. Liquidity measurement is important given the role of liquidity in affecting market functioning. For instance, Korn et al. (2019), formalizing the derivative hedge theory of Cho and Engle (1999), show that spot market illiquidity is not shifted in a one-to-one fashion to the futures market. Instead, it interacts with price risk, liquidity risk, and the risk aversion of the market maker.

Two measures of Bitcoin market liquidity are used - the high-low range (HLR) following Chung and Zhang (2014) and the volatility over volume (VoV) index developed by Fong et al.

(2017). The high-low range (HLR) is computed by adjusting the Chung and Zhang (2014) measure by replacing bid and ask prices with the high and low prices, such that:

$$HLR_t = \frac{H_t - L_t}{0.5\,(H_t + L_t)} \tag{6}$$

The volatility over volume (VoV) index (Fong et al. 2017) is defined as:

$$VoV_t = \frac{\ln\left({}^{H_t}/_{L_t}\right)}{\sqrt{volume}} \tag{7}$$

Therefore, we employ a comprehensive set of liquidity measures.

A significant impediment in the calculation of Bitcoin liquidity lies in the use of reported trading volumes by Bitcoin exchanges. There are studies that document the problem of suspicious trading activity and inflated trading volumes on Bitcoin exchanges. Several reasons have been attributed for this phenomenon, such as the need to attract more customers, convince coin producers to host their ICO's by over-emphasizing exchange liquidity (Wan, 2019) and price manipulation by exchanges (Gandal et al., 2018).

To ensure the validity of our liquidity measures that use reported Bitcoin trading volumes, we check for potential anomalies in trading volumes using Benford's law, a well-documented technique in fraud detection. The Law argues that numbers in a series consistently follow a pattern with low digits occurring more frequently in initial positions than larger digits. Given its efficacy in detecting anomalies in almost any series of numbers, the Law has been applied to a variety of settings, ranging from natural sciences (see for instance, Sambridge et al., 2010) to auditing (Drake and Nigrini, 2000) and accounting (Papanikolaou and Grammatikos, 2020). Interestingly, recent applications of the Benford's Law include cryptocurrency markets (Cong et al., 2019; Peterson, 2020)[6].

Figure 2 shows the Benford distributions, both actual and theoretical (the red dashed line). Benford results at least for our sample period suggest the presence of no significant anomalies in Bitcoin volumes, reassuring us of the validity of our liquidity results that use reported Bitcoin trading volumes.

2.3. Methodology

In this study we quantify the impact of a discrete event (a treatment), i.e., the introduction of bitcoin futures on the Bitcoin spot market. The causal impact of an event is the difference between the observed value of the response variable and the unobserved value that would have been obtained had the intervention not taken place (Brodersen et al. 2015; Claveau 2012; Hoover 2012; Antonakis et al. 2010). We use several sources of information to quantify the causal effect of the launch of bitcoin futures. First, the behaviour of Bitcoin spot market itself, prior to the introduction of futures[7]. Second, the behaviour of potential control variables, that are not directly affected by the intervention but are correlated with the variable of interest and were predictive of the target series prior to the intervention (for instance, return series for other cryptocurrencies). We also assume, that the correlation between the Bitcoin spot market and the control series continued after the launch of Bitcoin futures. . A post-treatment part of control time-series due to its potential to predict a dependent variable, Bitcoin spot market price, is also used. In our model, we use Bitcoin return, variance, volatility, skewness, kurtosis and liquidity as the treatment variables, y's, and the ones of Ethereum and Litecoin as controls. Ethereum and Litecoin are chosen due to their correlation with bitcoin and absence of bitcoin futures effect on their efficiency (Köchling et

[6] For a comprehensive review on the use of Benford's Law in Finance and Accounting, see Flayyih et al. (2020).

[7] The pre-intervention period starts on 1st July 2017 due to data availability and continues till 18th December 2017, which is treated as the day of the event or intervention.

al. 2018). Following Brodersen et al. (2015) we built a diffusion-regression (state-space) structural time-series model, where one component of state is a regression that prevents a inflexible commitment to a particular control variables implemented by integrating a posterior uncertainty regarding influence of selected predictors as well as an uncertainty about which predictors to include. It has the following advantages, i.e., (i) it allows for different types of assumptions regarding the latent state and emission processes underlying the observed cryptocurrency data, including local trends and seasonality; (ii) it gives flexibility posterior inferences can be summarised because of an application of Bayesian approach to inferring the temporal evolution of Bitcoin spot market; (iii) the selected approach allows for using a spike-and-slab prior on regression counterpart in the structural time-series model, allowing to average over the selected controls; (iv) avoids overfitting. Using this model, the posterior distribution of the Bitcoin spot market return, volatility, skewness, kurtosis and liquidity are derived given the value of the target series in the pre-Bitcoin futures introduction period and the values of the controls (Ethereum and Litecoin markets) after the introduction of the futures. Deducting the predicted values from the observed response in the post-intervention period derives a semiparametric Bayesian posterior distribution for the causal effect.

Typically, Bayesian structural time-series models are very flexible and can be specified in general as the following pair of equations. An observation equation that describes how a given system state translates into measurements:

$$y_t = Z_t^T a_t + \varepsilon_t \tag{8}$$

and a state equation that specifies the transition process of latent variables from one time point to the next:

$$a_{t+1} = T_t a_t + R_t \eta_t \tag{9}$$

where y_t is observed data, a_t is a latent *d*-dimensional state vector (formed by concatenating the individual state components), Z_t^T is a *d*-dimensional output vector, where d is the total number of latent states for all entries in y_t, ε_t is a scalar observation error with noise variance *σt*, *ηt* is a *q*-dimensional system error with a *q*×*q* block-diagonal state-diffusion matrix *Qt* , where *q* ≤ *d*, T_t is a *d* × *d* transition matrix, R_t is a *d* × *q* control matrix (*q* ≤ *d),* $\varepsilon_t \sim \mathcal{N}(0, \sigma_t^2)$, $\eta_t \sim \mathcal{N}(0, Q_t)$ are independent of all other coefficients, $R_t \eta_t$ is the error structure allows for incorporation of state components of less than full rank.

Structural time series models built in terms of components have a direct interpretation (Qiu, Jammalamadaka and Ning 2018). The model incorporates several such the components. The first component is a local linear trend with a slope that exhibits stationarity:

$$\mu_{t+1} = \mu_t + \delta_t + \eta_{\mu,t} \tag{10}$$

$$\delta_{t+1} = D + \rho(\delta_t - D) + \eta_{\delta,t} \tag{11}$$

where μ_t is the trend at time *t,* δ_t is the expected increase in *μ* between times *t* and *t* + 1, the slope of the time trend is AR(1) variation around a long-term slope of *D*, |ϱ| < 1 is the learning rate at which the local trend is updated. Thus, the model accounts for both short-term and long-term information. ρ is a *m* x *m* diagonal matrix with diagonal entries $0 \leq \rho_{ii} \leq 1$, for i=1; 2; … ; m, and represent the learning rates at which the local trend is updated for y_t. When $\rho_{ii} = 1$, the corresponding slope becomes a random walk. In general, the specification of time series models for the trend component differs due to the time-series characteristics and any prior knowledge.

The next component catches seasonality an is incorporated as

$$\gamma_{t+1} = -\sum_{s=0}^{S-2} \gamma_{t-s} + \eta_{\gamma,t} \tag{12}$$

where S represents the number of seasons, and γ_t is their joint contribution to the observed response y_t. The part of the transition matrix T_t that represent seasonality is an (Si-1)x(Si -1) matrix with -1 along the top row, 1 along the subdiagonal and 0 elsewhere. We estimated and tested the models with an S = 7 day-of-week effect, as well as an S = 52 weekly annual cycle. The results show not significant different in estimation of the Bitcoin futures introduction effect.

One of the popular ways to include control time series (Ethereum and Litecoin) in the model is through a linear regression with either static or dynamic coefficients. A starting point is s static regression, that can be presented in state-space form as $Z_t = \beta^T x_t$ and $a_t = 1$, where x_t is the set of predictors at time t, and β represents corresponding static regression coefficients. It is assumed that all covariates are contemporaneous, meaning that no lag between Bitcoin (treated time series) and Ethereum and Litecoin (untreated time series) are imposed.

Alternatively, contemporaneous covariates with dynamic regression coefficients can be used to calculate accurate predictions of control time series that received no treatment and are used when the linear relationship between treated and control time-series is believed to change over time.

It is represented as

$$x_t^T \beta_t = \sum_{j=1}^{J} x_{j,t}\, \beta_{j,t} \tag{13}$$

$$\beta_{j,t+1} = \beta_{j,t} + \eta_{\beta,j,t} \tag{14}$$

where $\beta_{j,t}$ is the coefficient for the j th control series, $\sigma^2_{\beta_j}$ is the standard deviation of its associated random walk and $\eta_{\beta,j,t} \sim \mathcal{N}(0, \sigma^2_{\beta_j})$, $Zt = \mathbf{x}t$ and $at = \beta t$, the corresponding part of the transition matrix is $Tt = I_{J\times J}$, with $Qt = diag\ (\sigma^2_{\beta_j})$. Setting in state-space form by $Zt = \beta^{\mathrm{T}}\mathbf{x}_t$ and $a_t = 1$ we end up with a static regression that allows for capturing local behaviour and accounting for regression effects. The state-space model is assembled following Brodersen et al. (2015). Local variability in the Bitcoin time series is captured by the dynamic local level or dynamic linear trend component.

Due to expectations of high degree of sparsity (Qiu et al. 2018), the spike-and-slab prior is applied which avoids overfitting (George and McCulloch 1993, 1997; Scott and Varian 2014). Also, a spike-and-slab prior over coefficients allows for a model to choose an appropriate set of coefficients. This prior combines the "spike", point mass at zero for an unknown subset of zero coefficients, with the "slab", that is a weakly informative distribution of nonzero coefficients, which is close to a Gaussian with a large variance (Brodersen et al. 2015). Forward-filtering, backward sampling framework is utilized to efficiently implement a spike-and-slab prior and thus to identify a sparse set of covariates from a set of data (Scott and Varian 2014). We can define the spike-and-slab prior as

$$p\left(\varrho, \beta, \frac{1}{\sigma^2_\varepsilon}\right) = p(\varrho)p(\sigma^2_\varepsilon|\varrho)p\left(\beta_\varrho\middle|\varrho, \sigma^2_\varepsilon\right) \tag{15}$$

where β_ϱ are nonzero elements of the vector β, $\varrho = (\varrho_1, \ldots, \varrho_J)$, $\varrho_j = 1$ if $\beta_j \neq 0$ and $\varrho_j = 0$ otherwise. The spike part of Eq.(15) can be defined as an arbitrary distribution over $\{0,1\}^J$ and can be calculated as a product of independent Bernoulli distributions:

$$p(\varrho) = \prod_{j=1}^{J} \pi_j^{\varrho j}(1-\pi_j)^{1-\varrho j} \tag{16}$$

where π_j is the prior probability of regressor *j* included in the model, that can be set as $\pi_j = M/J$, where *M* is the expected model size (Scott and Berger 2010).

The "slab" part of the prior is based on a normal-inverse Gamma distribution (Brodersen et al. 2015):

$$\beta_\varrho | \sigma_\varepsilon^2 \sim \mathcal{N}\left(b_\varrho, \sigma_\varepsilon^2 \left(\Sigma_\varrho^{-1}\right)^{-1}\right) \tag{17}$$

$$\frac{1}{\sigma_\varepsilon^2} \sim \mathcal{G}\left(\frac{v_\varepsilon}{2}, \frac{s_\varepsilon}{2}\right) \tag{18}$$

where b_ϱ is prior expectation about the value of each element of β, Σ_ϱ^{-1} denote the rows and columns of Σ^{-1} corresponding to nonzero entries in ϱ, v_ε is the number of observations worth of weight the prior estimate should be given, $s_\varepsilon = v_\varepsilon(1-R^2)s_y^2$, $R^2 \in [0,1]$. Applying Zellner's (1986) g-prior, $\Sigma^{-1} = \frac{g}{n}X^T X$ allows to interpret *g* as *g* observations worth of information. Then, to ensure propriety Σ^{-1} can be written as follows with default values of $g = 1$ and $w = ½$ (Brodersen et al. 2015):

$$\Sigma^{-1} = \frac{g}{n}\{wX^T X + (1-w)\ diag\ (X^T X)\} \tag{19}$$

For posterior simulation a Gibbs sampler is used to simulate a sequence $(\theta,a)^{(1)}, (\theta,a)^{(2)}, \ldots$ from a Markov chain whose stationary distribution is $p(\theta,a|\mathbf{y}1:n)$.

For posterior inference the following steps are done (Brodersen et al. 2015). First, draws of the model parameters θ and the state vector a are simulated given the observed data $\mathbf{y}_{1:n}$. For this purpose, a Gibbs sampler is applied to simulate a sequence $(\theta,\alpha)^{(1)}$, $(\theta,\alpha)^{(2)}$, . . . from a Markov chain whose stationary distribution is $p(\theta,\alpha \mid y1 : n)$. We draw the latent state from given model parameters and $\tilde{Y}$, using the posterior simulation algorithm from Durbin and Koopman (2002) that uses the Kalman filter and a fast mean smoother. To draw of the static regression coefficients β we apply:

$$\varrho|\dot{y}_{1:n} \sim C(\dot{y}_{1:n}) \frac{|\Sigma_{\varrho}^{-1}|^{1/2}}{|V_{\varrho}^{-1}|^{1/2}} \frac{p(\varrho)}{S_{\varrho}^{(\frac{N}{2})-1}} \tag{20}$$

were $\dot{y}_{1:n}$ denote y_t with the contributions from the other state components subtracted away, $C(\dot{y}_{1:n})$ is an unknown normalizing constant, $V_{\varrho}^{-1} = (X^T X)_{\varrho} + \Sigma_{\varrho}^{-1}$, $S_{\varrho} = s_{\varepsilon} + \dot{y}^{T}{}_{1:n}\dot{y}_{1:n} + b_{\varrho}^{T}\Sigma_{\varrho}^{-1}b_{\varrho} - \tilde{\beta}_{\varrho}^{T}V_{\varrho}^{-1}\tilde{\beta}_{\varrho}$, $\tilde{\beta}_{\varrho} = \left(V_{\varrho}^{-1}\right)^{-1}(X_{\varrho}^{T}\dot{y}_{1:n} + \Sigma_{\varrho}^{-1}b_{\varrho})$, $N = v_{\epsilon} + n$. We use a Gibbs sampler that draws each ϱ_j given all other ϱ_{-j} and then once it is complete, we sample directly from $p(\beta, \frac{1}{\sigma_{\varepsilon}^{2}}, \dot{y}_{1:n})$ by applying standard conjugate formulae.

Then, the posterior simulations are applied to simulate from the posterior predictive distribution $p(\tilde{y}_{n+1:m}|y_{1:n}, x_{1:n})$ over the time series $\tilde{y}_{n+1:m}$ given the observed activity before intervention $\mathbf{y}_{1:n}$. Finally, the posterior predictive samples are used for calculation of the posterior distribution of the pointwise impact for each time, *t*. The posterior distribution of cumulative impact is derived using the same samples.

Causal impact estimation deals with the posterior incremental effect, $p(\tilde{y}_{n+1:m}|y_{1:n}, x_{1:m})$. Therefore, the Bitcoin market response is $\tilde{y}_{n+1}, \dots \tilde{y}_m$ that would have been observed in the treated (spot) market, after the intervention, in the absence of treatment.

The posterior probability that the intervention had any effect and checking whether the posterior interval for the effect includes zero is expressed in terms of a *p*-value[8]. Based on the calculated results, we evaluate impact (Brodersen et al. 2015). First, samples from the approximate posterior predictive density of the effect attributed to the intervention (pointwise impact) is yield:

$$\phi_t^{(\tau)} \coloneqq y_t - \tilde{y}^{(\tau)}{}_t \tag{21}$$

where $t = n+1, \ldots, m$. Then, the cumulative effect of the introduction of futures over time is calculated:

$$\sum_{t'=n+1}^{t} \phi_{t'}^{(\tau)} \tag{22}$$

Eq. (22) represents cumulative sum of causal increments that approaches its true total value (in expectation) as we increase the forecasting period. This cumulative impact can also be calculated as running average effect:

$$\frac{1}{t-n} \sum_{t'=n+1}^{t} \phi_{t'}^{(\tau)} \tag{23}$$

that eventually approach zero. The results of usage of Eqs. (21-23) are then depicted.

2.4. Descriptive Statistics

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[8] Based on parameter priors and the data provide, the posterior distribution of the response variable that would be expected in the absence of an intervention is calculated and compared to the actual response. The tail-area probability is the probability under the calculated posterior that the response is at least as extreme as the observed one the tail-area probability is small, the effect of the intervention can be considered significant.

Descriptive statistics of different cryptocurrency returns are reported in Table 1. Here one can see that the Bitcoin and Ethereum offer the highest and negative mean returns, respectively. Litecoin appears to be the riskiest, in terms of variance, skewness and kurtosis. It has a kurtosis value of 18.71 as against 3 for a normal distribution, indicating very high probability of extreme values and fluctuations in returns.

3. Empirical results and discussion

We estimate the Bayesian diffusion-regression (state-space) structural time-series model with student distribution where the effects on the selected parameters of the Bitcoin market are presented below.

The pre-intervention period starts on 1st July 2017 due to data availability and continues till 18th December 2017, which is treated as the day of the event or intervention.[9] We select the following event windows for the post-intervention period - 1 day, 3 days, 1 week, 1-6 months, and 22 months (the end date of observations). The results and statistics are reported in Table 2 (Table 2a contains the main results, while Tables 2b and 2c have the results of using 2h and 4h raw data for robustness check; in general results are robust to selected frequencies), while results for individual variables are presented in Figures 1 to 18.

3.1. Effect on USD Bitcoin spot market return

The estimates of the Bitcoin return with and without the introduction of futures are presented in Panel A of Table 2. The Brodersen (2015) technique compares realized returns post-launch to 'inferred' returns in the absence of intervention. We notice that while realized returns remain consistently negative, the model predicts consistent positive returns in the absence of

[9] A short pre-treatment period can potentially cause fails in recognition of important patterns in our data and wider posterior intervals (i.e., an underpowered analysis).
Regarding the end of a pre-treatment period, for robustness, we also estimate our results for the intervention day of 10th December 2017 and have very similar results. We do not report them to conserve space but are available upon request from the corresponding author.

Bitcoin futures. For instance, on the next day after the introduction of bitcoin futures, Bitcoin return in the USD spot market had an average value of approx. -0.0015. In the absence of the introduction of bitcoin futures, one could expect an average return of 0.0016 (p=0.00). Subtracting the model-generated predicted value from the realized value provides us with an estimate of the causal effect of the intriduction of futures on US spot bitcoin return, which equals -0.0031.

Similarly, coefficients on the 'causal effect of the intervention' represent the average impact the introduction of Bitcoin futures had on the spot USD Bitcoin market returns, calculated as indicatd above. We see that for upto about 6 months after launch, the effect remains significantly negative, though its intensity diminishes over time. It is interesting to see that the adverse impact on Bitcoin returns starts right from day 1 after the launch. This seems to suggest that the spot USD Bitcoin market might have been better off without the launch of futures in terms of generation of better returns.

These findings are reiterated by Figures 3 and 4. In Figure 3, one notices that the negative impact of the launch of Bitcoin futures on spot returns diminishes over time and becomes rather stable after the third month or so.

3.2. Effect on realized variance and volatility of the USD Bitcoin spot market

3.2.1 Effect on realized variance

Results are presented in Panel B of Table 2. This time we observe a positive variance for both the realized as well as the predicted series, though realized variance values always remain higher than predicted ones. Once again, the main coefficients of interest are those on 'the causal effect of the intervention' that indicate the average impact of the launch of Bitcoin futures on spot realized variance.

The effect of the introduction of the bitcoin futures on the USD Bitcoin spot market realized variance is positive, which indicates that on average, futures ended up making the Bitcoin spot market riskier (similar results are documented by Blau and Whitby, 2019). Also, this effect peaks at about 1 week and remains statistically significant for up to 6 months' post-launch. The heightened volatility in the Bitcoin market on account of Bitcoin futures can be observed in the 6-month numbers, where realized variance has an average value of approx.. 0.0043. as opposed to the expected value in the absence of an intervention, which is 0.0022. The latter is almost half the size of the actual value observed.

In the 22-month post-intervention period, realized variance has an average value of approx. 0.0022 while in the absence of an intervention, the expected value is 0.0017. The causal effect is 0.00047. Though still positive, this effect is not statistically significant.

Figure 5 presents the same pattern. One observes a sharp rise in realized variance right from day 1 after the launch which continues till about 1 week, after which a downward trend sets in. At about 22 months, one notices an almost complete drop of variance to normal (pre-launch) levels.

3.2.2. Effect on realized volatility and stochastic volatility with leverage, heavy tails and jumps

Panel C of Table 2 and Figures 7 and 8 present results about realized volatility. The introduction of Bitcoin futures significantly increased Bitcoin market volatility, right from the first day after launch. The effect continues and reaches its peak after one week of the introduction of futures, after which it begins to fall. In terms of statistical results, realized volatility in the USD Bitcoin spot market has an average value of approx. 0.016 at the end of the first week after introduction of futures, with an expected value in the absence of an intervention of0.0037 (p=0.00). The causal impact of the introduction of futures therefore is the difference in values, 0.012, statistically significant at the 1% level. This positive effect on realized volatility, however, remains statistically significant till about the fifth month after the introduction. Similar to results for realized variance, the positive impact of futures on realized volatility fades away at about 22 months after launch.

Our robustness results using the SV model indicate that an on an overall basis, a stochastic volatility model with leverage, heavy tails and jumps reveals similar patterns in realized volatility as GARCH models used in this study. (see Fig. 9-10) One key difference, however, is that unlike realized volatility, it does not reveal similar patterns of peaks. Taking into account both realized volatility and the SV model for robustness, we can say that the introduction of Bitcoin futures has had a positive and significant effect on spot market volatility until the fifth month after introduction..[10]

While interpreting these results, one should keep in mind the fact that increased volatility following the launch of futures is not necessarily an undesirable outcome. Spot market volatility may rise as a consequence of better information transmission from the futures to the cash markets, following the launch of futures (Ross, 1989). However, with these results, one cannot dismiss the destabilization hypothesis associated with the launch of Bitcoin futures. This hypothesis postulates that the possibility of short selling encourages higher speculation on the part of speculative, uninformed investors that contributes to higher spot market volatility. In other words, armed with the ability to short-sell operate at higher levels of leverage and lower transaction costs, badly-informed investors introduce noise into the price-discovery process.

In the context of Bitcoin, Kapar and Olmo (2019) find that the Bitcoin futures market dominates the price discovery process, implying enhanced speculative activity affecting spot prices. Gulen and Maydew (2000) on the other hand, offer a country-level perspective to analysing the futures-spot volatility relationship. They find that the introduction of futures results in heightened volatility in the stock markets of the US and Japan, the only two countries that exhibit such behaviour out of the 25 studied. They attribute the results to Stein's (1987) information-based model in which prices are determined through the interaction between hedgers and informed speculators in the stock market. While the availability of futures facilitates greater risk-sharing and

[10] The results from the GARCH models (simple GARCH, tGARCH, GARCH-in-means, etc.) show the similar pattern. The best fit

consequently, reduced volatility, this effect could be potentially offset by greater noise and chaos created by hedgers in response to a noisy, informative signal.

In the end, one could conclude that the ultimate effect of futures on underlying spot market volatility is a function of the state of development of the concerned economy's financial institutions. For highly-developed markets such as the US, the introduction of futures offers only a modest stabilization mechanism (compared to the already-existing mechanisms in the market) when compared to the additional noise created in trading (Black, 1986; De Long et al., 1990 etc.). Thus, based on Gulen and Maydew (2000), we conclude that our results support the destabilization hypothesis that states that the introduction of futures increased volatility in the underlying spot market, consequently destabilizing it (Cox, 1976; Cagan, 1981; Hart and Kreps, 1986; Stein, 1987; etc).

3.3. Effect on realized skewness of the USD Bitcoin spot market

Panel D of Table 2 and Figures 11 and 12 present the results of the impact of the launch of bitcoin futures on realized skewness in the USD spot Bitcoin market. This time we observe a negative and positive series for realized and predicted skewness across time periods. This results in a general negative overall impact of the introduction of Bitcoin futures on realized skewness across time, which starts right from the first day after launch, results are statistically significant only starting 3 days' post-launch and peaks at 1 week post-launch. The effect diminishes over time but continues to remain statistically significant until the first month after launch. Given the absence of statistical significance after 1 month, the remaining post-intervention period cannot be meaningfully interpreted.

During the one-month post-intervention period, the realized skewness of the USD Bitcoin return has an average value of approx. -0.14, while the predicted value is 0.29 (p=0.039). The causal effect of the launch of Bitcoin futures on realized skewness is therefore, -0.43. Broadly speaking, this implies that the introduction of futures decreases the degree of asymmetry of the Bitcoin return distribution around its mean. Without Bitcoin futures, the USD Bitcoin spot market return would have been distributed with an asymmetric tail extending towards more positive values. This means that in terms of skewness in Bitcoin returns, the introduction of Bitcoin futures can be considered to have been beneficial to the development of the Bitcoin spot market.

One of the possible explanations of this phenomenon can be based on the volatility feedback model (French et al. 1987; Pindyck 1983; Nelson 1990; Engle and Ng 1993; Glosten et al. 1993; etc) that both good and bad news contribute to uncertainty in terms of future prices. That makes risk-averse investors require a higher rate of return and a lower present price to reward the higher risks, regardless of the nature of the news. This feedback effect reinforces the effect of the negative impact of bad news and restrains the effect of the positive impact of good news.

According to the theories of skewness preferences (Mitton and Vorkink, 2007; Barberis and Huang, 2008) investors prefer positive skewness due to overpricing of positively skewed equities. Lien and Wang (2015) show that an increase in skewness reduces the demand for hedging, meaning that the introduction of bitcoin futures can potentially increase such a demand. Also, our results for the bitcoin market support the finding of Bris, Goetzmann, and Zhu (2007), that markets where going short is not practiced, market returns display significantly less negative skewness.

3.4. Effect on realized kurtosis of the USD Bitcoin spot market

The effect of the introduction of futures on realized kurtosis flows a rather unusual pattern (see Panel E of Table 2, Figures 13 and 14). While the causal impact is negative up to the first week after introduction of futures, it flips signs thereafter. From the end of the first month post-launch, one observes that the introduction of futures actually ended up increasing realized kurtosis in the USD Bitcoin spot market. Not only is this positive effect significant, it continues to grow and intensify till the 22nd month after launch.

Indeed, during the first week of the post-intervention period, the realized kurtosis of the USD Bitcoin spot market return had an average value of approx. 2.56, with a predicted value of

3.32 in the absence of the introduction of futures. This results in a causal impact of -0.76 (significant at 5%) that the launch of futures had on realized kurtosis in the Bitcoin market.

Overall, this trend seems to suggest that while futures may have helped in reducing kurtosis in the early periods of their launch, they ended up making the Bitcoin spot market more vulnerable to extreme swings and fluctuations eventually. This is an interesting result since it points towards the role of Bitcoin futures in exacerbating the already notorious, extreme behaviour of the Bitcoin market.

3.5. Effect on liquidity of the Bitcoin market

3.5.1. Liquidity, high-low range HLR (Chung and Zhang 2014)

Results are presented in Figures 15-16 and Panel F of Table 2. Realized liquidity values indicate falling liquidity over time. Causal effects of the launch of Bitcoin futures suggest a generally positive impact of the launch of Bitcoin futures on spot market liquidity, with statistical significance observed only for the 3-day and the 1-week post-intervention period. Not only this, one also notices an upward trend in the positive impact on liquidity up to the first week, after which values begin to decline. This seems to suggest that an overall mildly positive impact of the launch of futures on Bitcoin spot market liquidity.

During the one-week post-intervention period, HLR had an average value of approx. 0.036 (Figures 11-12, Panel F of Table 2). By contrast, in the absence of futures, the model-generated predicted value is 0.025. The causal effect of the introduction of Bitcoin futures on market liquidity is therefore 0.010 (significant at 1%).

3.5.2. Fong et al. (2017) liquidity measurement

Results are presented in Figures 17-18 and Panel G of Table 2. One observes trends similar to those for the Chung and Zhang (2014) liquidity measure. Even when generally speaking, the launch of futures appears to have increased spot market liquidity, statistical significance is observed only for the 1-week and 1-month post-intervention periods. After 1-month post-launch, the positive effect rapidly dissipates.

During the one-month post-intervention period, the VoV index had an average value of approx. 0.0029 as opposed to a predicted value of 0.0016, in the absence of futures. The causal effect of Bitcoin futures on market liquidity using the VoV index equals 0.0012 (p=0.00).

After 22 months of the post-intervention period, the VoV index has an average value of approx. 0.00074, and a predicted value of 0.00089 in the absence of Bitcoin futures. This generates a causal impact of -0.00014 on account of the event. Despite the negative sign observed, the absence of any statistical significance makes it impossible to deduce the actual impact.

Thus, one could conclude that the introduction of Bitcoin futures had a statistically significant positive effect on the liquidity of the USD Bitcoin spot market, but not large enough to stabilize the highly illiquid market.

4. Conclusion

The academic literature on Bitcoin is ever-growing and has been dominated by studies determining the market dynamics of the cryptocurrency as well as debating whether Bitcoin is a currency, an asset or even a commodity. With the introduction of the futures market in December 2017, bitcoin investors can now short the Bitcoin spot market and implement hedging strategies much easily than before. Although the literature to date has focused on the impact of the futures market on price discovery and the immediate impact on the spot price, we examine what impact the introduction of Bitcoin futures has had on five attributes of the Bitcoin spot market – returns, liquidity, volatility, skewness and kurtosis. We answer this question by implementing a Bayesian diffusion-regression (state-space) structural time-series model.

Our results indicate that the introduction of bitcoin futures ended up lowering USD bitcoin spot market returns and skewness, and driving up Bitcoin market volatility, kurtosis and liquidity. Even when the only positive outcome associated with the introduction of Bitcoin futures is the rise in liquidity in the spot market, the effect is too small to make any real difference in terms of stabilizing the market. Given this, we find support in favour of the hypothesis that the introduction of bitcoin futures, in general, contributed to destabilizing the USD bitcoin spot market (Cox, 1976; Cagan, 1981; Hart and Kreps, 1986; Stein, 1987).

Specifically, for a few days following the introduction of the futures, an increase in spot market volatility is observed. The phenomenon reaches its peak after one week of the introduction of futures, after which it begins to fall. On an overall basis however, volatility in the USD bitcoin spot market after the introduction of futures is significantly higher than one could expect without futures. The introduction of bitcoin futures decreases skewness - the degree of asymmetry of the return distribution around its mean - which can be interpreted as an increase in demand for hedging (Lien and Wang, 2012). Also, our skewness results are in line with the findings of Bris, Goetzmann, and Zhu (2007), who postulate that in markets where the possibility of short-selling is absent, market returns display significantly less negative skewness. The launch of Bitcoin futures ended up making the Bitcoin spot market not only more volatile but also more vulnerable to extreme return values. This can be witnessed from sharp increases in realized kurtosis values of the USD bitcoin spot market.

These significant changes to return and volatility characteristics of the USD Bitcoin spot market brought about by the introduction of Bitcoin futures imply a whole new risk-return regime for investors in this market. Our results can help foster this understanding by facilitating a comparison of risk-return characteristics before and after the launch of Bitcoin futures. Since its inception in 2008, despite its baffling volatility and price swings, the Bitcoin market has lured investors with its too-good-to-believe returns that remain unmatched with any other asset class in the financial market. However, lower returns and heightened volatility brought about by Bitcoin futures could potentially deter risk-averse investors from participating in the market.

Not only in terms of overall volatility, even changes in skewness and kurtosis could affect investor participation in the Bitcoin. Guidolin and Timmermann (2008) show that investors have skewness and kurtosis preferences. Kurtosis measures the fatness of tails in the return distribution. Thus, risk-averse investors may want to avoid holding assets with higher kurtosis given the likelihood of extreme returns.

Our results hold value even in terms of regulation and policy making. As the debate surrounding the worthiness of Bitcoin futures continues, academic literature continues to investigate and document the impact that the newly launched derivative instruments have had on the cryptocurrency market in general and the Bitcoin market in particular. For instance, while Bitcoin futures make it possible for investors to short-sell the Bitcoin with margin requirements far below those that existed before (Baur and Dimpfl, 2019), result in higher market stability (Kim et al., 2020) and improves informational efficiency (Kochling et al., 2019), they are not free from externalities in terms of other cryptocurrencies. For instance, the launch of Bitcoin futures has been associated with higher tail risk of other cryptocurrencies (Sebastiao and Godinho, 2020) and even higher levels of volatility for non-Bitcoin cryptocurrencies (Blau and Whitby, 2019).

Given that Bitcoin futures affect not only the immediate USD Bitcoin spot market (as we have documented) but the overall crypto market as well, regulation of these futures merits significant policy attention, despite all other benefits that they may entail.

However, we suggest that our results be interpreted with caution given the fact that the period from 2017-end to 2018 has been extraordinary in terms of the cryptocurrency market. Not only did prices demonstrate extreme and unprecedented swings during this period, but a significant milestone was witnessed through the introduction of Bitcoin futures. Given the presence of various confounding events that occurred during this time, it becomes difficult to make a causal assessment of the introduction of futures on the spot market, given that in different or 'more stable' conditions, this impact could easily have been different.

In short, our overall findings suggest that a destabilizing impact of the launch of bitcoin futures on the USD bitcoin spot market. Through our findings on the individual impact of Bitcoin futures on the various dimensions of the USD Bitcoin spot market – returns, liquidity, volatility, skewness and kurtosis, our results offers insights for existing and potential investors in the Bitcoin and capital market regulators who may need to timely control the externalities associated with this controversial innovation.

References

Abadie, A. (2005). Semiparametric difference-in-differences estimators. Review of Economic Study 72, 1–19.

Abadie, A. and Gardeazabal, J. (2003). The economic costs of conflict: A case study of the Basque country. American Economic Review 93, 113–132.

Abadie, A., Diamond, A. and Hainmueller, J. (2010). Synthetic control methods for comparative case studies: Estimating the effect of California's tobacco control program. Journal of American Statistic Assoc. 105, 493–505.

Akyildirim, E., Corbet, S., Lucey, B., Sensoy, A., Yarovaya, L. (2020). The relationship between implied volatility and cryptocurrency returns. *Finance Research Letters* 33.

Alexander J. C. (2009) Remarks on the use of Benford's law. Available at SSRN 1505147

Alexander, C., Choi, J., Park, H., Sohn, S. (2019). BitMEX bitcoin derivatives: Price discovery, informational efficiency, and hedging effectiveness. *Journal of Futures Markets*, forthcoming.

Alexander, C., Dakos, M. (2020) A critical investigation of cryptocurrency data and analysis. *Quantitative Finance, 20(2),* 173-188.

Amaya, D., Christoffersen, P., Jacobs, K. and Vasquez, A. (2011). Do realized skewness and kurtosis predict the cross-section of equity returns? CREATES research paper. p. 3-7.

Andersen, T. G., & Bollerslev, T. (1998). Answering the skeptics: Yes, standard volatility models do provide accurate forecasts. *International Economic Review* 39(4), 885-905.

Andersen, T. G., & Todorov, V. (2010). Realized volatility and multipower variation. In R. Cont (Ed.), *Encyclopedia of quantitative finance* (pp. 1494-1500). New York: Wiley.

Andersen, T. G., Bollerslev, T., & Diebold, F. X. (2007). Roughing it up: Including jump components in the measurement, modeling and forecasting of return volatility. *The Review of Economics and Statistics* 89(4), 701-720.

Andersen, T. G., Bollerslev, T., & Huang, X. (2011a). A reduced form framework for modelling volatility of speculative prices based on realized variation measures. *Journal of Econometrics* 160(1), 176-189.

Andersen, T. G., Bollerslev, T., & Meddahi, N. (2011b). Realized volatility forecasting and market microstructure noise. *Journal of Econometrics* 160(1), 220-234.

Andersen, T. G., Bollerslev, T., Diebold, F. X., & Labys, P. (2003). Modeling and forecasting realized volatility. *Econometrica* 71(2), 579-625.

Andersen, T. G., Dobrev, D. and Schaumburg, E. (2012). Jump-robust volatility estimation using nearest neighbor truncation. *Journal of Econometrics*, 169 (1), 75-93.

Ang, A., Hodrick, R.J., Xing, Y., Zhang, X. (2006) The cross-section of volatility and expected returns. *Journal of Finance* 61, 259-299.

Antonakakis, N., Chatziantoniou, I. and Gabauer, D. (2019) Cryptocurrency Market Contagion: Market Uncer-tainty, Market Complexity, and Dynamic Portfolios. *Journal of International Financial Markets, Institutions and Money* 61,37–51

Antonakis, J., Bendahan, S., Jacquart, P. and Lalive, R. (2010). On making causal claims: A review and recommendations. *Leadership Quarterly*, 21 1086–1120.

Antoniou, A., Foster, A.J. (1992) The effect of futures trading on spot price volatility: Evidence for Brent crude oil using GARCH. *Journal of Business Finance & Accounting* 19, 473-484.

Antoniou, A., Holmes, P. (1995) Futures trading, information and spot price volatility: Evidence for the FTSE-100 stock index futures contract using GARCH. *Journal of Banking and Finance* 19, 117-129.

Antoniou, A., Holmes, P., Priestley, R. (1998) The effects of stock index futures trading on stock index volatility: An analysis of the asymmetric response of volatility to news. *Journal of Futures Market* 8, 151-166.

Antoniou, A., Koutmos, G. and Pericli, A. (2005) Index futures and positive feedback trading: evidence from major stock exchanges. *Journal of Empirical Finance* 12(2), 219-238.

Bacha O., Vila A. (1994). Futures markets, regulation and volatility: The case of the Nikkei stock index futures markets. *Pacific Basin Finance Journal* 2, 201 – 225.

Baklaci, H., Tutek, H. (2006) The impact of the futures market on spot volatility: An analysis in Turkish derivatives markets Computational Finance and its Applications II (2006).

Barberis, N. and Huang, M. (2008) Stocks as lotteries: the implications of probability weighting for security prices. *Am. Econ. Rev.* 98, 2066-2100.

Bariviera, A. F. (2017). The inefficiency of Bitcoin revisited: A dynamic approach. *Economics Letters*, 161, 1-4.

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

Baur, D.G., Dimpfl, T. (2019). Price discovery in bitcoin spot or futures? *The Journal of Futures Markets* 39(7), 803-817.

Black, F. (1986) Noise. *Journal of Finance*, 41, 529-543.

Blau, B. M. & Whitby R. J. (2019). The Introduction of Bitcoin Futures: An Examination of Volatility and Potential Spillover Effects. *Economics Bulletin*, 39(2), 1030-1038.

Bohl, M.T., Diesteldorf, J. and Siklos, P.L. (2015) The effect of index futures trading on volatility: Three markets for Chinese stocks. *China Economic Review* 34, 207-224.

Bohl, M.T., Salm, C.A. and Wilfling, B. (2010) Do individual index futures investors destabilize the underlying spot market? *The Journal of Futures Market* 31(1), 81-101.

Bohl, M.T., Stephan, P.M. (2013). Does Futures Speculation Destabilize Spot Prices? New Evidence for Commodity Markets. *Journal of Agricultural and Applied Economics* 45(4), 595-616.

Bologna, P., Cavallo, L. (2002) Does the introduction of stock index futures effectively reduce stock market volatility? Is the 'future effect' immediate? Evidence from the Italian stock exchange using GARCH. *Applied Financial Economics* 12, 183-192.

Borri, N. (2019). Conditional tail-risk in cryptocurrency markets. *Journal of Empirical Finance*, 50, 1-19.

Bouri, B., Roubaud, D., Shahzad, S. J. H. (2020) Do Bitcoin and other cryptocurrencies jump together? *The Quarterly Review of Economics and Finance* 76, 396-409.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., Hagfors, L. I. (2017). On the hedge and safe-haven properties of bitcoin: Is it really more than a diversifier? *Finance Research Letters*, 20, 192-198.

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

Bray, M. (1981). Futures trading, rational expectations, and the efficient markets hypothesis. *Econometrica* 49, 575–596.

Brière, M., Oosterlinck, K., Szafarz, A. (2015). Virtual currency, tangible return: Portfolio diversification with bitcoin. *Journal of Asset Management*, 16, 365-373.

Bris, A., Goetzmann, W.N. and Zhu, N. (2007). Efficiency and the Bear: Short Sales and Markets Around the World. The Journal of Finance LXII(3), 1029-1079.

Brodersen, K. H., Gallusser, F., Jim Koehler, J., Remy, N., Scott, S.L. (2015). Inferring causal impact using Bayesian structural time-series models. *The Annals of Applied Statistics* 9(1), 247–274.

Cagan, P. (1981). Financial futures markets: Is more regulation needed? *Journal of Futures Markets*, 1, 169–190.

Catania, L., Grassi, S., Ravazzolo, F. (2019). Forecasting cryptocurrencies under model and parameter instability. *International Journal of Forecasting*, 35, 485-501.

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

Chance, D. M., Brooks, R. (2013). An introduction to derivatives and risk management (9th edition). Mason, OH: South-Western, Cengage Learning

Chang, E.C., Cheng, J.W., Pinegar, J.M. (1999). Does futures trading increase stock market volatility? The case of the Nikkei Stock Index futures markets. *Journal of Banking and Finance*, 23 (5), 727-753.

Chen, C., Gerlach, R., Lin, E., & Lee, W. (2011). Bayesian forecasting for financial risk management, pre and post the global financial crisis. *Journal of Forecasting* 31(8), 661-687.

Chen, H., Han, Q., Li, Y., & Wu, K. (2013). Does index futures trading reduce volatility in the Chinese stockmarket? A panel data evaluation approach. *Journal of Futures Markets*, 33(12), 1167–1190.

Cho, Y. and Engle, R. (1999). Modeling the Impacts of Market Activity on Bid-Ask Spreads in the Option Market. Working paper, National Bureau of Economic Research, 7331.

Chung, K.H., and Chuwonganant, C. (2018) Market volatility and stock returns: the role of liquidity providers. *Journal of Financial Markets* 37, 17-34.

Chung, K.H., Zhang, H. (2014). A simple approximation of intraday spreads using daily data. *J. Finance Mark.* 17, 94–120.

Claveau, F. (2012). The Russo–Williamson Theses in the social sciences: Causal inference drawing on two types of evidence. *Stud. Hist. Philos. Biol. Biomed. Sci.*, 43 806–813.

Cong, Lin and Li, Xi and Tang, Ke and Yang, Yang, Crypto Wash Trading (December 30, 2019). Available at SSRN: https://ssrn.com/abstract=3530220 or http://dx.doi.org/10.2139/ssrn.3530220.

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

Corbet, S., Lucey, B., Urquhart, A., Yarovaya, L. (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis*, 62, 182-199.

Corsi, F., Mittnik, S., Pigorsch, C. & Pigorsch, U. (2008) The Volatility of Realized Volatility, *Econometric Reviews* 27:1-3, 46-78.

Corsi, F., Pirino, D., & Renò, R. (2010). Threshold bi-power variation and the impact of jumps on volatility forecasting. *Journal of Econometrics* 159(2), 276-288.

Cox, C. C. (1976). Futures trading and market information. *Journal of Political Economy* 84, 1215–1237.

Danthine, J.-P. (1978). Information, futures prices, and stabilizing speculation. *Journal of Economic Theory* 17, 79–98.

Darrat, A.F., Rahman, S. (1995) Has futures trading activity caused stock price volatility. *Journal of Futures Markets* 15, 537-557.

De Long, B.J., Shleifer, A., Summers, L.H., Waldman, R.J. (1990) Noise trader risk in financial markets. *Journal of Political Economy* 98, 703-738.

Degiannakis, S., Floros, C. (2013). Modeling CAC40 volatility using ultra-high frequency data. *Research in International Business and Finance* 28, 68-81.

Diebold, F. X., & Yilmaz, K. (2012). Better to give than to receive: Predictive directional measurement of volatility spillovers. *International Journal of Forecasting* 28(1), 57–66.

Diebold, F. X., & Yilmaz, K. (2016). Trans-Atlantic equity volatility connectedness: U.S. and European financial institutions, 2004–2014. *Journal of Financial Econometrics* 14, 81–127.

Durbin, J. and Koopman, S.J. (2002). A simple and efficient simulation smoother for state space time series analysis. *Biometrika* 89(3), 603-616.

Engle, R. F., & Gallo, G. M. (2006). A multiple indicators model for volatility using intra-daily data. *Journal of Econometrics* 131(1), 3-27.

Engle, R.F. and Ng, V.K. (1993). Measuring and Testing the Impact of News on Volatility. *Journal of Finance* 45, 7-38.

Fang, H., & Lai, T. Y. (1997). Co-kurtosis and capital asset pricing. Financial Review 32, 293–307.

Flayyih, H.H., Noorullah, A. S., Jari, D.-A. S. and Hasan, A. M. (2020). Benford Law: A Fraud Detection Tool Under Financial Numbers Game: A Literature Review. *sshj* 4(5), 1909-1914.

Fong, K.Y.L., Holden, C.W., Tobek, O. (2017). Are volatility over volume liquidity proxies useful for global or US research. Kelley School of Business Research Paper No. 17-49.

Fong, L. and Han, C. (2015). Impacts of derivative markets on spot market volatility and their persistence. *Applied Economics* 47(22), 2250-2258.

Fortenbery, T.R., Zapata, H.O. (1997) An evaluation of price linkages between futures and cash markets for cheddar cheese. *The Journal of Futures Markets* 17, 279-301.

Fostel, A., Geanakoplos, J. (2012). Tranching, CDS, and Asset Prices: How Financial Innovation Can Cause Bubbles and Crashes. *American Economic Journal: Macroeconomics* 4(1), 190–225.

French, K.R., Schwert, R. Stambaugh, G.F. (1987) Expected stock returns and volatility. *Journal of Financial Economics* 19, 3-29

Freris, A.F. (1990) The effects of the introduction of stock index futures on stock prices: The experience of Hong Kong 1984–1987 S.G. Rhee, R.P. Chang (Eds.), Pacific-Basin Capital Markets Research, Elsevier, Amsterdam (1990)

Fruehwirt, W., Hochfilzer, L., Weydemann, L., Roberts, S. (2020) Cumulation, Crash, Coherency: A Cryptocurrency Bubble Wavelet Analysis. *Finance Research Letters*. In Press. doi: https://doi.org/10.1016/j.frl.2020.101668

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

George and McCulloch (1997). Approaches for Bayesian variable selection. *Statistica sinica*, 339-373.

George, E. I. and Mcculloch, R. E. (1993). Variable selection via Gibbs sampling. *J. Amer. Statist. Assoc.* **88** 881–889.

George, E. I. and Mcculloch, R. E. (1997). Approaches for Bayesian variable selection. *Statist. Sinica* **7** 339–374.

Gilbert, S., Jones, S.K., Morris, G.H. (2006) The impact of skewness in the hedging decision *J. Futures Markets* 26, 503-520.

Glosten, L. R., Jagannathan, R., and Runkle, D. E. (1993). On the relation between the expected value and the volatility of the nominal excess return on stocks. *The Journal of Finance* 48, 1779–1801.

Gonzalez, M.O., Jareno F. and Skinner, F.S. (2020) Nonlinear Autoregressive Distributed Lag Approach: An Application on the Connectedness between Bitcoin Returns and the Other Ten Most Relevant Cryptocurrency Returns. *Mathematics* 8(5) ttps://doi.org/10.3390/math8050810

Guidolin, M., & Timmermann, A. (2008). International asset allocation under regime switching, skew, and kurtosis preferences. Review of Financial Studies 21, 889–935.

Gulen H., Mayhew S. (2000). Stock index futures trading and volatility in international equity markets. *The Journal of Futures Markets* 20(7), 661 – 685.

Gupta, A., Varma, P. (2016). Impact of Futures Trading on Spot Markets: An Empirical Analysis of Rubber in India. *Eastern Economic Journal* 42(3), 373–386.

Hale, G., Krishnamurthy, A., Kudlyak, M., Shultz, P. (2018). How futures trading changed Bitcoin prices. *FRBSF Economic Letter*. 2018-12.

Harris, L. (1989) S&P 500 Cash stock price volatilities. *The Journal of Finance* 44, 1155-1175.

Hart, O. D., & Kreps, D. M. (1986). Price destabilizing speculation. *Journal of Political Economy*, 94, 927–952.

Harvey A.C., Shephard N (1996). Estimation of an Asymmetric Stochastic Volatility Model for Asset Returns. *Journal of Business & Economic Statistics* 14(4), 429–434.

Hattori T., Ishida R. (2019) Did the introduction of Bitcoin futures crash the Bitcoin market at the end of 2017? Available at SSRN, 2019.

Hoover, K. D. (2012). Economic theory and causal inference. In Philosophy of Economics 13 (U. Mäki, ed.) 89–113. Elsevier, Amsterdam.

Hudson, R., Urquhart, A. (2019). Technical trading and cryptocurrencies. *Annals of Operations Research*, forthcoming.

Jacquier E, Polson NG, Rossi P.E. (2004). Bayesian Analysis of Stochastic Volatility Models with Fat-Tails and Correlated Errors. *Journal of Econometrics* 122(1), 185–212.

Jegadeesh, N. and Subrahmanyam, A. (1993) Liquidity Effects of the Introduction of the S&P 500 Index Futures Contract on the Underlying Stocks. *The Journal of Business* 66(2), 171-187.

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

Jochum, C., Kodres, L. (1998) Does the introduction of futures on emerging market currencies destabilize the underlying currencies? International Monetary Fund. Working Paper, February.

Kajtazi, A., Moro, A. (2019). The role of bitcoin in well diversified portfolios: A comparative global study. *International Review of Financial Analysis*, 61, 143-157.

Kapar, B. and Olmo, J (2019) An analysis of price discovery between Bitcoin futures and spot markets. *Economics Letters* 174, 62-64

Kapar, B., Olmo, J. (2019). An analysis of price discovery between Bitcoin futures and spot markets. *Economics Letters* 174, 62-64.

Kasman A., Kasman S. (2008) The impact of futures trading on volatility of the underlying asset in the Turkish stock market. *Physica* A 387, 2837 – 2845.

Katsiampa, P. (2017). Volatility estimation for Bitcoin: A comparison of GARCH models. *Economics Letters*, 158, 3-6.

Katsiampa, P., Corbet, S., Lucey, B. (2019). High frequency volatility co-movements in cryptocurrency markets. *Journal of International Financial Markets, Institutions and Money*, forthcoming.

Kawaller, I., Koch, P., Koch, T. (1987) The temporal price relationship between S&P 500 futures and the S&P 500 index. *Journal of Finance* 42, 1309-1329.

Kim S., Shephard N., Chib S (1998). Stochastic Volatility: Likelihood Inference and Comparison with ARCH Models. *The Review of Economic Studies* 65(3), 361–393.

Kim, W., Lee, J., Kang, K. (2019). The effects of the introduction of Bitcoin futures on the volatility of Bitcoin returns. *Finance Research Letters* (in Press)

Kim, W., Lee, J., Kang, K. (2020). The effects of the introduction of Bitcoin futures on the volatility of Bitcoin returns. *Finance Research Letters* 33.

Köchling, G., Müller, J., Posch, P.N. (2019). Does the introduction of futures improve the efficiency of Bitcoin? *Finance Research Letters* 30, 367-370.

Korn, O., Krischak, P., Theissen. E. (2019). Illiquidity transmission from spot to futures markets. Journal of Futures Markets, 39(10), 1228-1249.

Koutmos, D. (2018) Return and Volatility Spillovers among Cryptocurrencies. *Economics Letters* 173, 122–27.

Koutmos, G., Tucker, M. (1996) Temporal relationships and dynamic interactions between spot and futures stock markets. *Journal of Futures Markets* 16, 55-69.

Kutan, A.M., Shi, Y., Wei, M., Zhao, Y. (2018) Does the introduction of index futures stabilize stock markets? Future evidence from emerging markets. *International review of Economics and Finance* 57, 183-197.

Kyle, A. S. (1985). Continuous auctions and insider trading. *Econometrica* 53, 1315–1336.

Laurent, S., Lecourt, C., & Palm, F. C. (2016). Testing for jumps in conditionally Gaussian ARMA–GARCH models, a robust approach. *Computational Statistics &Data Analysis* 100, 383–400.

Lee C., Tong H. (1998). Stock futures: the effects of their trading on the underlying stocks in Australia. *Journal of Multinational Financial Management* 8, 285 – 301.

Lee L., Stevenson S., Lee M (2014). Futures Trading, Spot Price Volatility and Market Efficiency: Evidence from European Real Estate Securities Futures. *The Journal of Real Estate Finance and Economics* 48(2), 299 – 322.

Lien, D. and Wang, Y. (2015) Effects of skewness and kurtosis on production and hedging decisions: a skewed t distribution approach. *Eur. J. Financ*e 21, 1132-1143

Liu, J., Wei, Y., Ma, F., & Wahab, M. I. M. (2017). Forecasting the realized range-based volatility using dynamic model averaging approach. *Economic Modelling* 61, 12-26.
Liu, R., Wan, S., Zhang, Z., and Zhao, X. (2019) Is the introduction of futures responsible for the crash of Bitcoin? *Finance Research Letters*, forthcoming.
Ma, F., Liu, J., Huang, D., & Chen, W. (2017). Forecasting the oil futures price volatility: A new approach. *Economic Modelling* 64, 560-566.
Matkovskyy, R. (2019). Centralized and decentralized bitcoin markets: Euro vs USD vs GBP. *Quarterly Rev. Econ. Finance* 71, 270–279.
Matkovskyy, R., Jalan, A. (2019). From Financial Markets to Bitcoin Markets: A Fresh Look at the Contagion Effect. *Finance Research Letters* 31, 93-97.
Matkovskyy, R., Jalan, A. (2020). Can Bitcoin Be an Inflation Hedge? Evidence from a Quantile-on-Quantile Model. Economic Review (in press).
Merton, R. C. (1980). On estimating the expected return on the market: An exploratory investigation. *Journal of Financial Economics* 8(4), 323-361.
Mitton, T., Vorkink, K. (2007) Equilibrium underdiversification and the preference for skewness.
Moratis, G. (2020) Quantifying the spillover effect in the cryptocurrency market. *Finance Research Letters.* In Press. Doi: 10.1016/j.frl.2020.101534
Nakajima J (2012). Bayesian Analysis of Generalized Autoregressive Conditional Heteroskedasticity and Stochastic Volatility: Modeling Leverage, Jumps and Heavy-Tails for Financial Time Series. *Japanese Economic Review* 63(1), 81–103.
Nakajima J, Omori Y (2012). Stochastic Volatility Model with Leverage and Asymmetrically Heavy-Tailed Error Using GH Skew Student's t Distribution." *Computational Statistics & Data Analysis* 56(11), 3690–3704.
Nakajima J., Omori Y. (2009). Leverage, Heavy-Tails and Correlated Jumps in Stochastic Volatility Models. *Computational Statistics and Data Analysis* 53(6), 2335–2353.
Nelson, D. B. (1990). Arch models as diffusion approximations. *Journal of Economics*, 45, 7–38.
Omori Y, Chib S, Shephard N., Nakajima J. (2007). Stochastic Volatility with Leverage: Fast and Efficient Likelihood Inference. *Journal of Econometrics* 140(2), 425–449.
Omori Y, Chib S, Shephard N., Nakajima J. (2007). Stochastic Volatility with Leverage: Fast and Efficient Likelihood Inference. *Journal of Econometrics* 140(2), 425–44;
Papanikolaou, N.I. and Grammatikos, T. (2020). Applying Benford's law to detect accounting data manipulation in the banking industry. *Journal of Financial Services Research.* (In Press)
Peterson, Timothy, To the Moon: A History of Bitcoin Price Manipulation (June 30, 2020). Available at SSRN: https://ssrn.com/abstract=3639431 or http://dx.doi.org/10.2139/ssrn.3639431
Pilar, C., Rafael, S. (2002) Does derivatives trading destabilize the underlying assets? Evidence from the Spanish stock market. *Applied Economics Letters* 9, 107-110.
Pindyck, R. S. (1983). Risk, inflation, and the stock market. NBER Working Paper 1186 National Bureau of Economic Research.
Platanakis, E., Urquhart, A. (2019). Should investors include Bitcoin in their portfolios? A portfolio theory approach. *British Accounting Review*, forthcoming.
Pok, W.C., Poshakwale, S. (2004) The impact of the introduction of futures contracts on the spot market volatility: The case of Kuala Lumpur stock exchange. *Applied Financial Economics* 14, 143-154.
Powers, M. J. (1970). Does futures trading reduce price fluctuations in the cash markets? *American Economic Review* 60, 460–464.
Qiu, J., Jammalamadaka, S.R., and Ning, N. (2018) Multivariate Bayesian Structural Time Series Model. *Journal of Machine Learning Research* 19, 1-33,
Rev. Financial Stud. 20, 1255-1288
Ruozhou, L., Shanfeng, W., Zili, Z., Xuejun, Z. (2020). Is the introduction of futures responsible for the crash of Bitcoin? *Finance Research Letters*, 34, 101259.

Ryoo, H.-J., Smith, G. (2004) The impact of stock index futures on the Korean stock market *Applied Financial Economics* 14, 243-251.

Santos, D. G., & Ziegelmann, F. A. (2014). Volatility forecasting via MIDAS, HAR and their combination: An empirical comparative study for IBOVESPA. *Journal of Forecasting* 33(4), 284-299.

Scharnowski, S. (2020). Understanding Bitcoin liquidity. *Finance Research Letters* 101477 (In press).

Schwert, W.G. (1990) Stock market volatility. *Financial Analysts Journal* (1990), 23-34.

Scott, S. L. and Varian, H. R. (2014). Predicting the present with Bayesian structural time series. *International Journal of Mathematical Modeling and Optimization* 5, 4–23.

Sebastião, H., Godinho, P. (2020). Bitcoin futures: An effective tool for hedging cryptocurrencies. *Finance Research Letters* 33.

Sensoy, A. (2019). The inefficiency of Bitcoin revisited: A high-frequency analysis with alternative currencies. *Finance Research Letters*, 28, 68-73.

Shen, D., Urquhart, A., Wang, P. (2020). Forecasting the volatility of Bitcoin: The importance of jumps and structural breaks. *European Financial Management*, 26, 1294-1323.

Shiller, R. J. (2017). What is bitcoin really worth? Don't even ask. *The New York Times,* https://www.nytimes.com/2017/12/15/business/bitcoin-investing.html.

Shynkevich, A. (2020) Bitcoin Futures, Technical Analysis and Return Predictability in Bitcoin Prices. Journal of Forecasting. In Press. https://doi.org/10.1002/for.2656

Sifat, I.M., Mohamad, A., Shariff, M.S.B. M. (2019) Lead-Lag relationship between Bitcoin and Ethereum: Evidence from hourly and daily data. *Research in International Business and Finance* 50, 306-321.

Smales, L.A. (2020) One Cryptocurrency to Explain Them All? Understanding the Importance of Bitcoin in Cryptocurrency Returns. *Economic Papers. Special Section: Economics of Blockchain Technology*, In Press. Doi: 10.1111/1759-3441.12282

Stein, J. C. (1987). Informational externalities and welfare-reducing speculation. *Journal of Political Economy*, 95, 1123–1145.

Stulz, R. (1996) Rethinking risk management. *J. Appl. Corporate Finance* 9(3), 8-24.

Tiwari, A. K., Jana, R. K., Das, D., Roubaud, D. (2018). Informational efficiency of Bitcoin – An extension. Economics Letters, 163, 106-109.

Tversky, A., Kahneman, D. (1992). Advances in prospect theory: Cumulative representation of uncertainty. *J. Risk Uncertainty* 5, 297–323.

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

Urquhart, A., Zhang, H. (2018). Is Bitcoin a hedge of safe-haven for currencies? An intraday analysis. *International Review of Financial Analysis*, 63, 49-57.

Vortelinos, D. I. (2017). Forecasting realized volatility: HAR against principal components combining, neural networks and GARCH. *Research in International Business and Finance* 39(B), 824-839.

Wan, C. (2019, May 28). Bitwise report: bitcoin is a 'significantly more efficient market' despite 95% fake volume. The Block.

Xie, S., Huang, J. (2014). The impact of index futures on spot market volatility in China. *Emerging Markets Finance and Trade* 50(S1), 167–177.

Xie, S., Mo, T. (2014). Index futures trading and stock market volatility in China: A difference-in-difference approach. *Journal of Futures Markets* 34(3), 282–297.

Yang, J., Balyeat, R.B., Leatham, D.J. (2005) Destabilizing effect of futures trading on agricultural commodity markets. *Journal of Business Finance and Accounting* 32(1-2), 297-323.

Yao, X. and Lio, Q. (2017) Effect of Crude Oil Futures Trading on Spot Market Volatility: A Panel Data–Based Counterfactual Prediction Analysis. *Emerging Markets Finance and Trade* 53(4), 918-931.

Yi, S., Xu, Z, Wang, G.-J. (2018) Volatility connectedness in the cryptocurrency market: Is Bitcoin a dominant cryptocurrency? *International Review of Financial Analysis* 60, 98-114.

Zellner, A. (1986). On assessing prior distributions and Bayesian regression analysis with prior distributions. In Bayesian Inference and Decision Techniques: Essays in Honor of Bruno de Finetti (P. K. Goel and A. Zellner, eds.). Stud. Bayesian Econometrics Statist. 6 233–243. North-Holland, Amsterdam. MR0881437

Zhong, M., Darraf, A.F., Otero, R. (2004) Price discovery and volatility spillovers in index futures markets: Some evidence from Mexico. *Journal of Banking & Finance* 28(12), 3037-3054.

Tables

Table 1: The descriptive statistics of the Bitcoin, Ethereum and Litecoin logarithmic returns.

	BTCUSD	ETHUSD	LTCUSD
mean	0.000060	-0.000020	0.000019
median	0.000050	0.000000	-0.000124
min	-0.111454	-0.135830	-0.138626
max	0.112861	0.141869	0.212333
variance	0.000097	0.000146	0.000187
SD	0.009854	0.012086	0.013657
skewness	0.181946	0.332911	0.807263
kurtosis	14.350840	15.996760	18.710240

Table 2a: This table presents the effect of the introduction and no introduction of Bitcoin futures on the Bitcoin spot price for returns, realized variance, realized volatility, stochastic volatility, realized kurtosis, realized skewness and liquidity. ***, ** and * indicate significance at the 1%, 5% and 10% respectively for the causal effect of the intervention.

	1 day	3 days	1 week	1 month	6 months	22 months
Panel A: Returns						
Introduction of Futures Markets	-0.0015	-0.0023	-0.0016	-0.00071	-0.00025	-0.000053
No Futures Markets	0.0016	0.00061	0.00029	0.00051	0.00043	0.00053
The causal effect of the intervention	-0.0031***	-0.0029 ***	-0.0019 ***	-0.0012***	-0.00068 *	-0.00059
P-value	0.00	0.00	0.00	0.00	0.10	0.26
Panel B: Realized Variance						
Introduction of Futures Markets	0.004	0.0082	0.015	0.0092	0.0043	0.0022
No Futures Markets	0.0027	0.0031	0.006	0.004	0.0022	0.0017
The causal effect of the intervention	0.0013**	0.0051***	0.0093***	0.0052***	0.002**	0.00047
P-value	0.07	0.001	0.001	0.001	0.089	0.456
Panel C: Realized Volatility						
Introduction of Futures Markets	0.005	0.0075	0.016	0.009	0.0036	0.0017
No Futures Markets	0.0017	0.0018	0.0037	0.0027	0.0018	0.0013
The causal effect of the intervention	0.0029 ***	0.0057 ***	0.012 ***	0.0063***	0.0019	0.00031
P-value	0.00	0.00	0.00	0.00	0.12	0.46
Panel D: Stochastic volatility with leverage, heavy tails and jumps						
Introduction of Futures Markets	0.0023	0.0025	0.0025	0.0026	0.002	0.0015
No Futures Markets	0.002	0.0021	0.0022	0.002	0.0018	0.0018
The causal effect of the intervention	0.00028***	0.00054***	0.00047***	0.00057***	0.000041	-0.00051
P-value	0.00	0.00	0.00	0.00	0.384	0.74
Panel E: Realized Skewness						
Introduction of Futures Markets	-0.057	-0.42	-0.32	-0.14	-0.03	-0.0077
No Futures Markets	0.47	0.24	0.27	0.29	0.2	0.24
The causal effect of the intervention	-0.52	-0.66***	-0.59*	-0.43**	-0.23	-0.25
P-value	0.24	0.01	0.08	0.04	0.12	0.33
Panel F: Realized Kurtosis						
Introduction of Futures Markets	2.16	2.72	2.56	4.55	4.93	5.52
No Futures Markets	3.37	3.41	3.32	3.59	3.41	3.57
The causal effect of the intervention	-1.21*	-0.69	-0.76**	0.96***	1.52***	1.95***
P-value	0.08	0.12	0.04	0.00	0.00	0.00
Panel G: Chung and Zhang (2014) Liquidity						
Introduction of Futures Markets	0.019	0.026	0.036	0.027	0.018	0.011
No Futures Markets	0.018	0.022	0.025	0.020	0.014	0.017
The causal effect of the intervention	0.001	0.0044*	0.010***	0.0074	0.0031	-0.0051
P-value	0.40	0.09	0.00	0.12	0.41	0.45
Panel J: Fong et al. (2017) Liquidity						
Introduction of Futures Markets	0.002	0.0019	0.0026	0.0029	0.0012	0.00074
No Futures Markets	0.0015	0.0017	0.002	0.0016	0.0012	0.00089
The causal effect of the intervention	0.000065	0.00021	0.00057***	0.0012***	0.000014	-0.00014
P-value	0.38	0.14	0.00	0.00	0.48	0.42

Table 2b: This table presents the effect of the introduction and no introduction of Bitcoin futures on the Bitcoin spot price for returns, realized variance, realized volatility, realized kurtosis, realized skewness and liquidity using 2 hour data.
***, ** and * indicate significance at the 1%, 5% and 10% respectively for the causal effect of the intervention.

	1 day	3 days	1 week	1 month	6 months	22 months
Panel A: Returns						
Introduction of Futures Markets	0.0032	-0.0045	-0.0055	-0.001	-0.00046	-0.00013
No Futures Markets	0.0027	0.00056	-0.0014	0.00035	0.00058	0.0004
The causal effect of the intervention	0.00043	-0.0051***	-0.0041***	-0.0014***	-0.001	-0.00053
P-value	0.41	0.002	0.001	0.0138	0.353	0.461
Panel B: Realized Variance						
Introduction of Futures Markets	0.002	0.0044	0.011	0.005	0.0022	0.0011
No Futures Markets	0.0013	0.0013	0.0035	0.002	0.0012	0.001
The causal effect of the intervention	0.00077***	0.003***	0.0071***	0.0029***	0.00097*	0.00014
P-value	0.013	0.001	0.001	0.001	0.13	0.483
Panel C: Realized Volatility						
Introduction of Futures Markets	0.0051	0.011	0.026	0.014	0.006	0.0031
No Futures Markets	0.0037	0.0039	0.0093	0.0061	0.003	0.0028
The causal effect of the intervention	0.0014**	0.0073***	0.016***	0.0077***	0.0024***	0.00031
P-value	0.097	0.001	0.001	0.001	0.034	0.442
Panel D: Realized Skewness						
Introduction of Futures Markets	-0.5	-0.76	-0.64	-0.14	-0.21	-0.09
No Futures Markets	-0.11	-0.13	-0.16	0.15	0.037	0.054
The causal effect of the intervention	-0.39	-0.63***	-0.48***	-0.3**	-0.25	-0.14
P-value	0.327	0.0173	0.029	0.1	0.223	0.411
Panel E: Realized Kurtosis						
Introduction of Futures Markets	2.51	2.41	2.45	3.39	3.81	3.92
No Futures Markets	2.96	2.88	2.77	2.95	2.89	2.95
The causal effect of the intervention	-0.45	-0.47	-0.32	0.44***	0.93***	0.96***
P-value	0.255	0.205	0.206	0.031	0.001	0.037
Panel F: Chung and Zhang (2014) Liquidity						
Introduction of Futures Markets	0.019	0.027	0.038	0.029	0.018	0.012
No Futures Markets	0.019	0.022	0.026	0.023	0.019	0.016
The causal effect of the intervention	-0.00021	0.0051***	0.012***	0.0064	-0.0011	-0.0042
P-value	0.487	0.0158	0.07	0.313	0.499	0.462
Panel G: Fong et al. (2017) Liquidity						
Introduction of Futures Markets	0.0017	0.002	0.0027	0.0024	0.0011	0.00074
No Futures Markets	0.0014	0.0015	0.0017	0.0016	0.0013	0.0012
The causal effect of the intervention	0.00035**	0.00054***	0.001***	0.00078	-0.00016	-0.00043
P-value	0.071	0.038	0.009	0.169	0.463	0.41

Table 2c: This table presents the effect of the introduction and no introduction of Bitcoin futures on the Bitcoin spot price for returns, realized variance, realized volatility, realized kurtosis, realized skewness and liquidity using 4 hour data.
***, ** and * indicate significance at the 1%, 5% and 10% respectively for the causal effect of the intervention.

	1 day	3 days	1 week	1 month	6 months	22 months
Panel A: Returns						
Introduction of Futures Markets	0.00054	-0.0092	-0.0096	-0.0035	-0.00096	-0.00029
No Futures Markets	0.0026	-0.00082	-0.002	-0.00044	0.0012	0.0015
The causal effect of the intervention	-0.0021*	-0.0084***	-0.0076***	-0.0031***	-0.0021	-0.0018
P-value	0.152	0.001	0.001	0.031	0.239	0.387
Panel B: Realized Variance						
Introduction of Futures Markets	0.00087	0.0026	0.0056	0.0025	0.0012	0.00056
No Futures Markets	0.00062	0.00093	0.0027	0.0013	0.00056	0.00026
The causal effect of the intervention	0.00025**	0.0017***	0.0029***	0.0012***	0.0006***	0.0003
P-value	0.084	0.001	0.001	0.001	0.024	0.343
Panel C: Realized Volatility						
Introduction of Futures Markets	0.0017	0.0098	0.027	0.013	0.0061	0.0028
No Futures Markets	0.0017	0.0028	0.011	0.0053	0.003	0.002
The causal effect of the intervention	0.000053	0.007***	0.017***	0.0082***	0.0031***	0.00074
P-value	0.467	0.001	0.001	0.001	0.007	0.422
Panel D: Realized Skewness						
Introduction of Futures Markets	-1.09	-1.12	-1.02	-1.02	-1.02	-0.21
No Futures Markets	0.38	0.27	-0.063	-0.063	-0.063	0.037
The causal effect of the intervention	-1.47***	-1.39***	-0.96***	-0.96***	-0.96***	-0.25
P-value	0.042	0.011	0.012	0.012	0.012	0.223
Panel E: Realized Kurtosis						
Introduction of Futures Markets	5.94	5.94	2.99	2.99	3.92	3.92
No Futures Markets	2.48	2.48	2.28	2.28	2.95	2.95
The causal effect of the intervention	3.45***	3.45***	0.71***	0.71***	0.96***	0.96***
P-value	0.001	0.001	0.006	0.006	0.037	0.037
Panel F: Chung and Zhang (2014) Liquidity						
Introduction of Futures Markets	0.015	0.028	0.03	0.028	0.018	0.011
No Futures Markets	0.016	0.021	0.024	0.021	0.015	0.014
The causal effect of the intervention	-0.00048	0.0066***	0.012***	0.0071	0.0022	-0.0033
P-value	0.451	0.054	0.01	0.245	0.453	0.468
Panel G: Fong et al. (2017) Liquidity						
Introduction of Futures Markets	0.0014	0.0019	0.0027	0.0023	0.0011	0.00072
No Futures Markets	0.0013	0.0014	0.0016	0.0015	0.0012	0.00097
The causal effect of the intervention	0.00014	0.00052***	0.0011***	0.00079	-0.0001	-0.0002
P-value	0.271	0.041	0.006	0.151	0.48	0.39

Figures

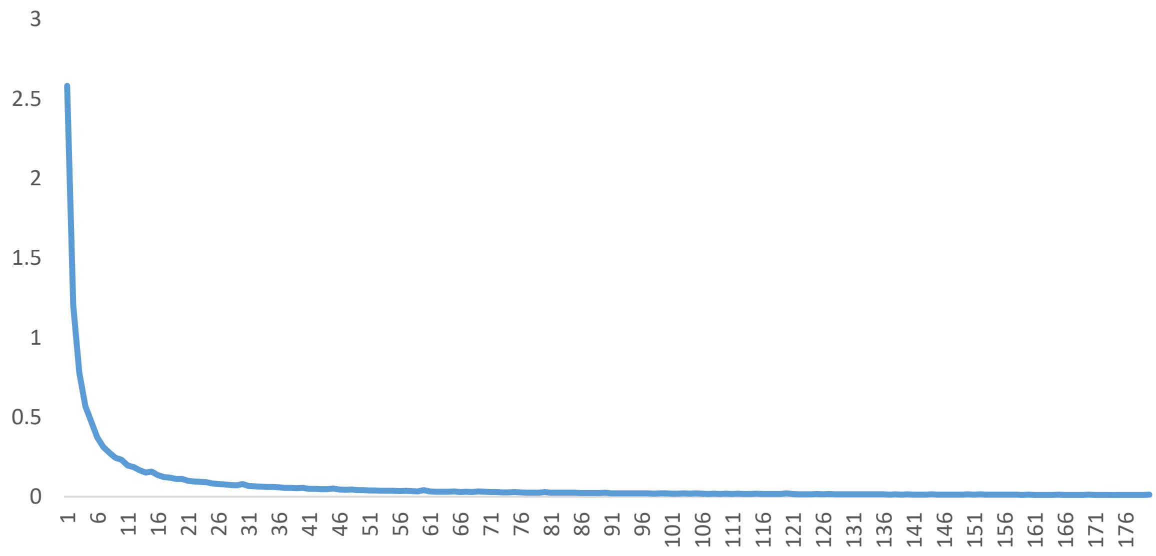
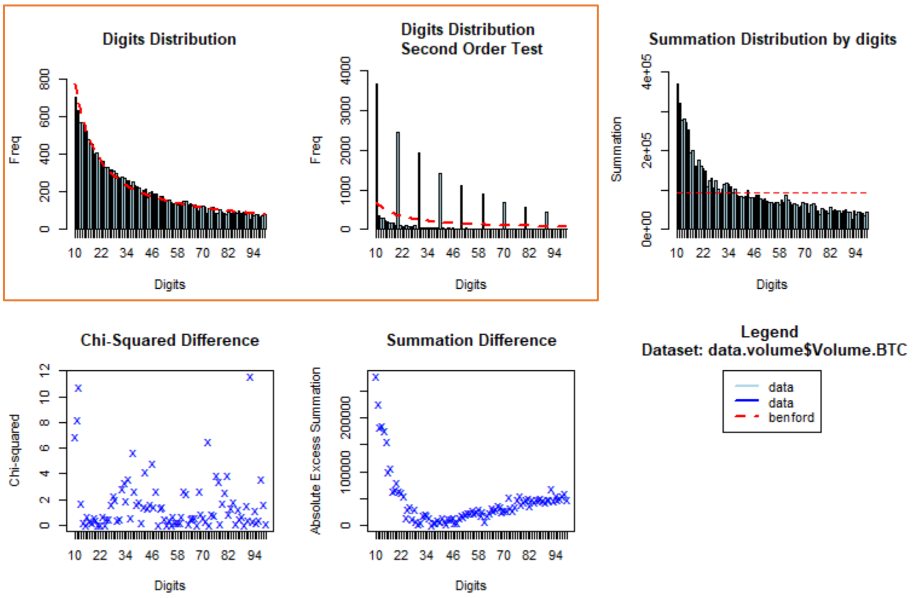
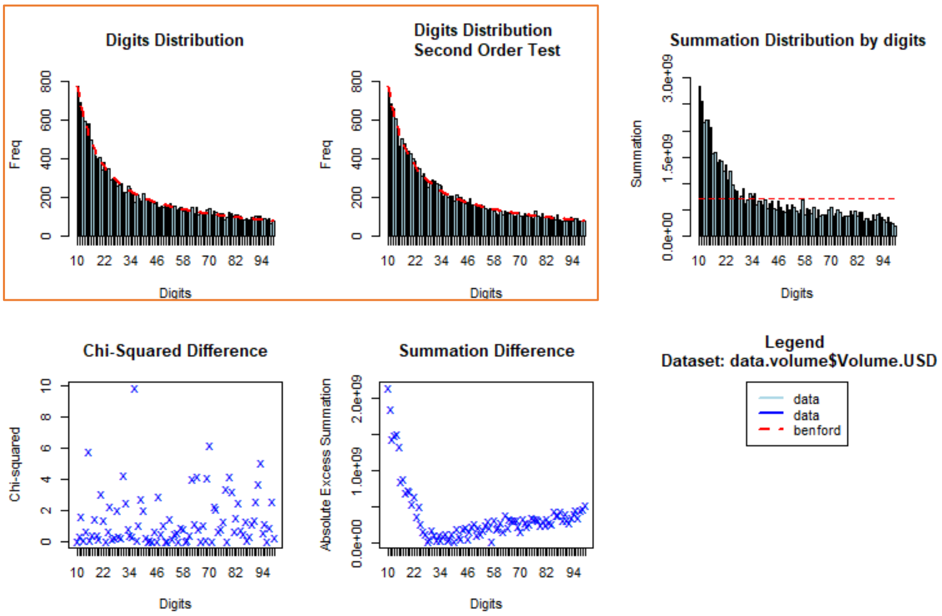


Figure 1: Volatility signature, bitcoin close prices.



Panel a) Volume in BTC



Panel b) Volume in USD

Figure 2: The Benford distributions of the bitcoin volumes (Panel (a) represents the volume in BTC, while Panel (b) represents the same volume in USD)

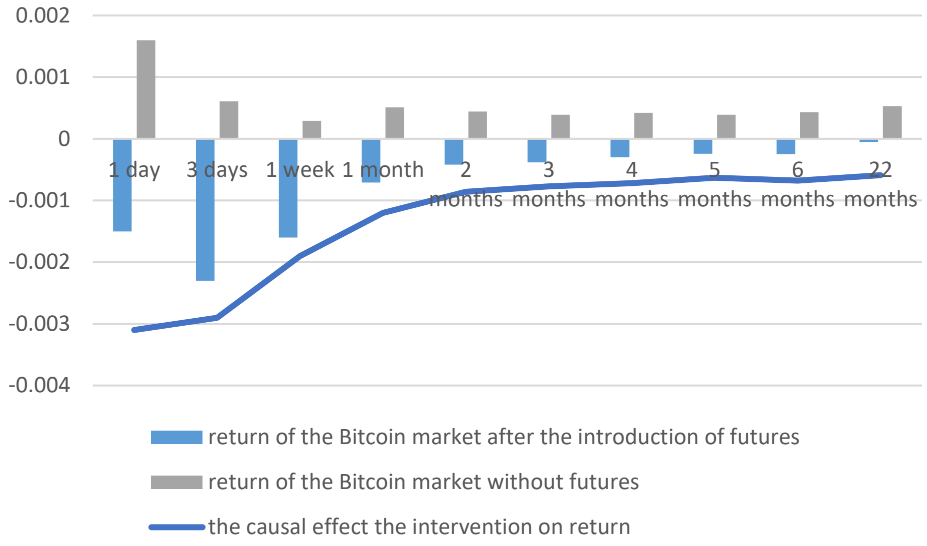


Figure 3: Dynamics of the USD Bitcoin spot market return with and without the introduction of Bitcoin futures (the y-axis values represent accumulative return of the Bitcoin spot market).

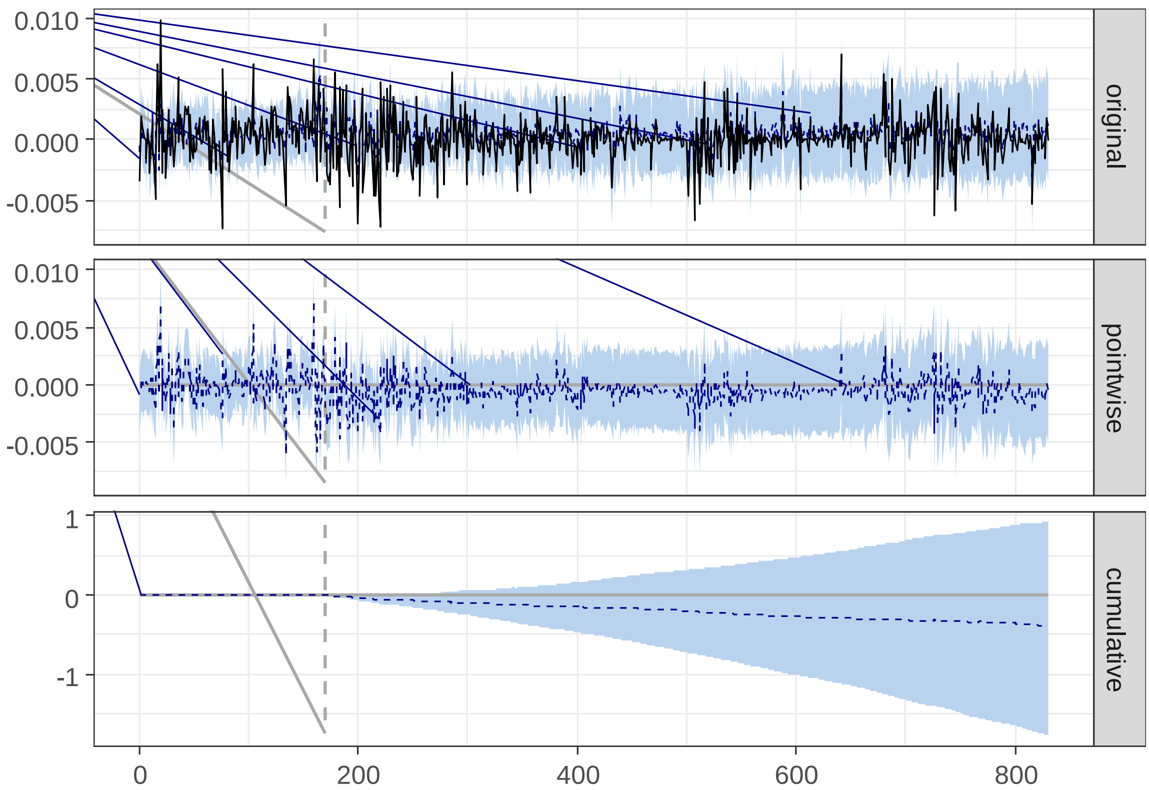


Figure 4: Inferring causal impact on USD Bitcoin spot market return through predictions, Bayesian Structural Time Series with student distribution. Two other markets (ETH and LTC, X1 and X2, respectively) were not subject to the intervention and thus are not included in the graph. A trajectory of a treated USD Bitcoin spot market return (Y) with an intervention on December 18th 2017. The difference between observed data of USD Bitcoin spot market return and predictions of this return is the inferred causal impact of the intervention. A cumulative impact of the introduction of Bitcoin futures on the Bitcoin USD spot market return (Posterior inferences, Eq. 22), for each day, the summed effect up to that day.

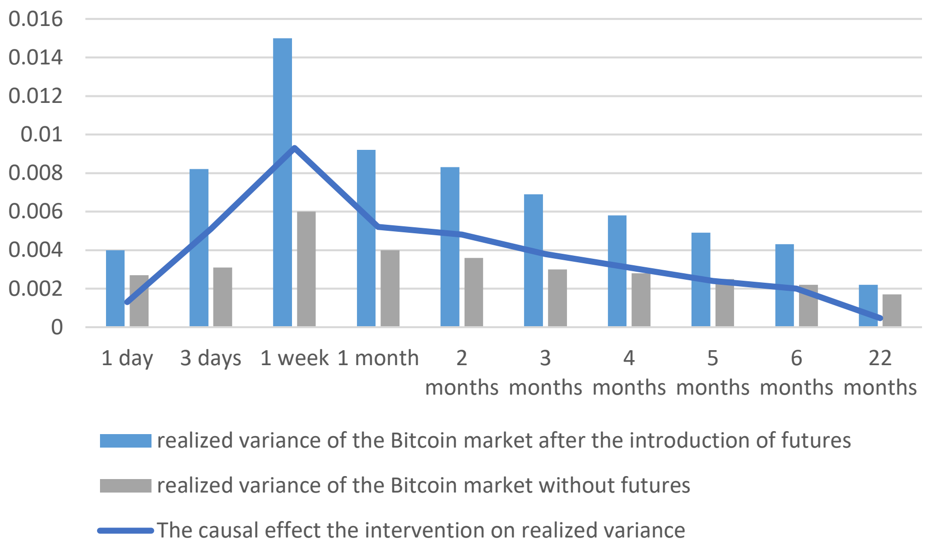


Figure 5: Dynamics of the realized variance of the USD Bitcoin spot market return with and without the introduction of the Bitcoin futures (the y-axis values represent accumulative realized variance of the Bitcoin spot market)

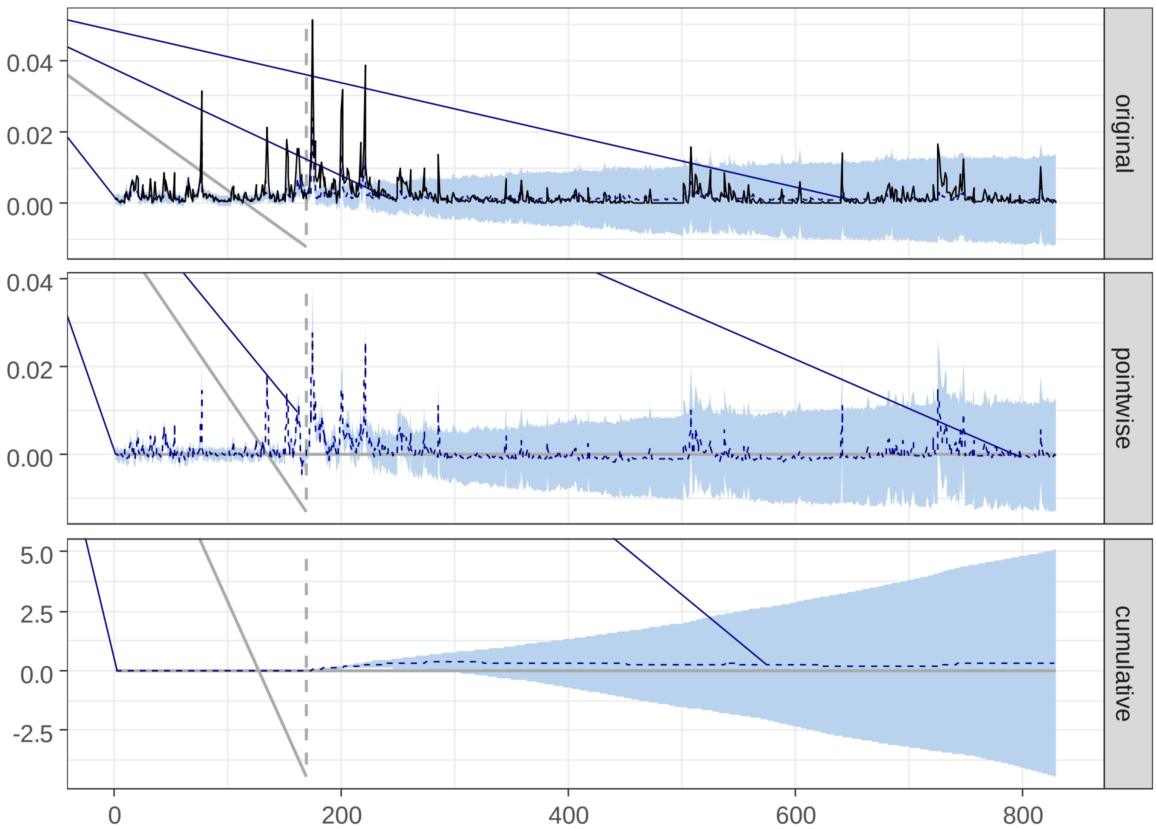


Figure 6: Inferring causal impact on USD Bitcoin spot market realized variance through predictions, Bayesian Structural Time Series with student distribution. Two other markets (ETH and LTC, X1 and X2, respectively) were not subject to the intervention and thus are not included in the graph. A trajectory of a treated USD Bitcoin spot market return (Y) with an intervention on December 18th 2017. The difference between observed data of USD Bitcoin spot market realized variance and predictions of this variance is the inferred causal impact of the intervention. A cumulative impact of the introduction of Bitcoin futures on the Bitcoin USD spot market realized variance (Posterior inferences, Eq. 22), for each day, the summed effect up to that day.

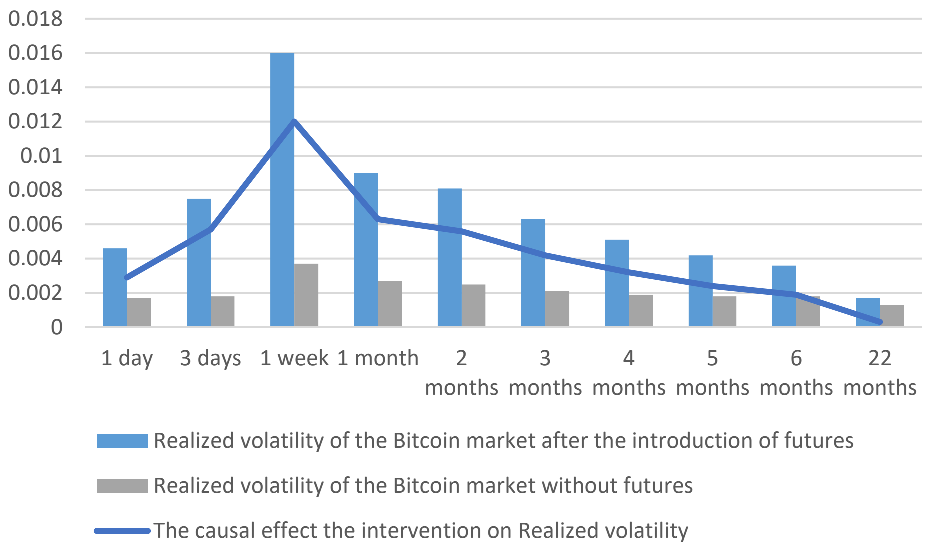


Figure 7: Dynamics of the realized volatility of the USD Bitcoin spot market return with and without the introduction of the Bitcoin futures (the y-axis values represent accumulative realized volatility of the Bitcoin spot market)

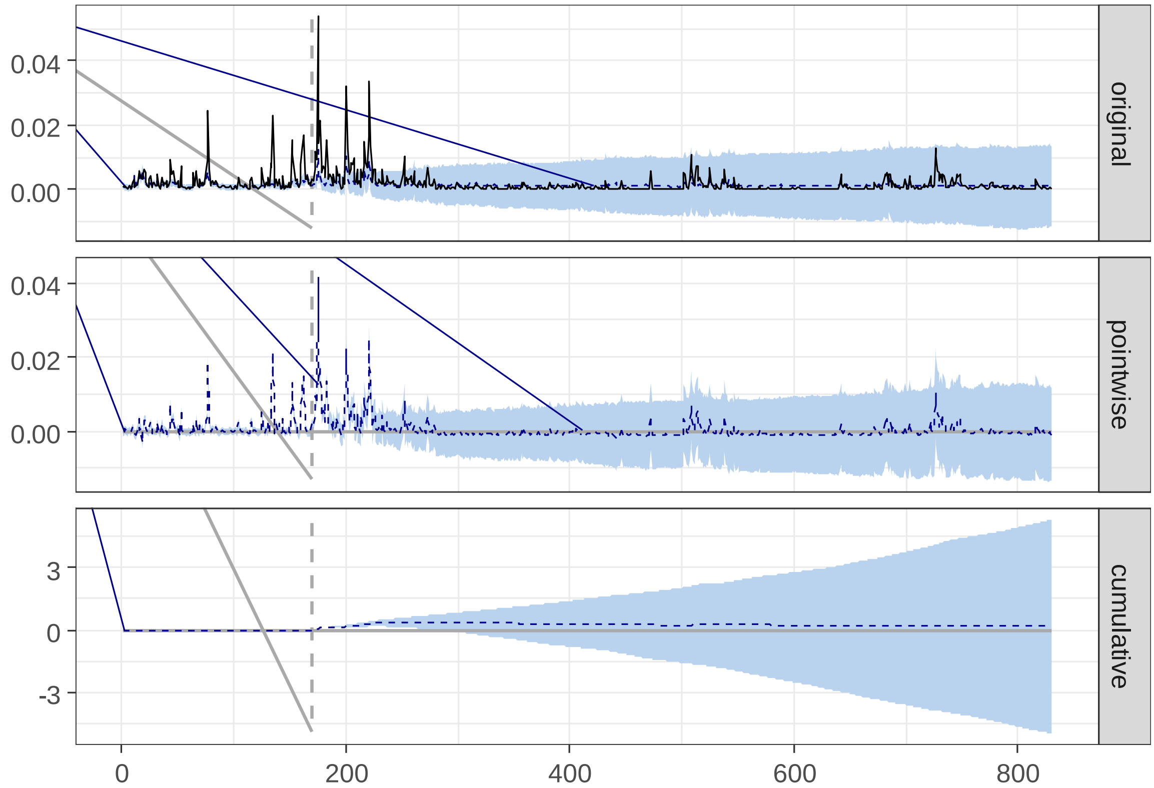


Figure 8: Inferring causal impact on USD Bitcoin spot market realized volatility through predictions, Bayesian Structural Time Series with student distribution. Two other markets (ETH and LTC, X1 and X2, respectively) were not subject to the intervention and thus are not included in the graph. A trajectory of a treated USD Bitcoin spot market realized volatility (Y) with an intervention on December 18th 2017. The difference between observed data of USD Bitcoin spot market realized volatility and predictions of this realized volatility is the inferred causal impact of the intervention. A cumulative impact of the introduction of Bitcoin futures on the Bitcoin USD spot market realized volatility (Posterior inferences, Eq. 22), for each day, the summed effect up to that day.

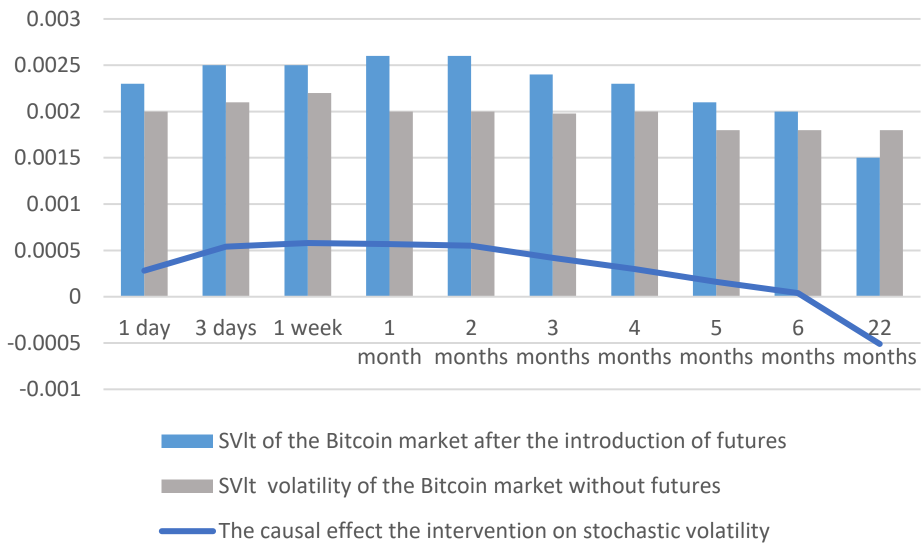


Figure 9: Dynamics of the stochastic volatility with leverage, heavy tails and jumps of the USD Bitcoin spot market return with and without the introduction of the Bitcoin futures (the y-axis values represent accumulative stochastic volatility of the Bitcoin spot market)

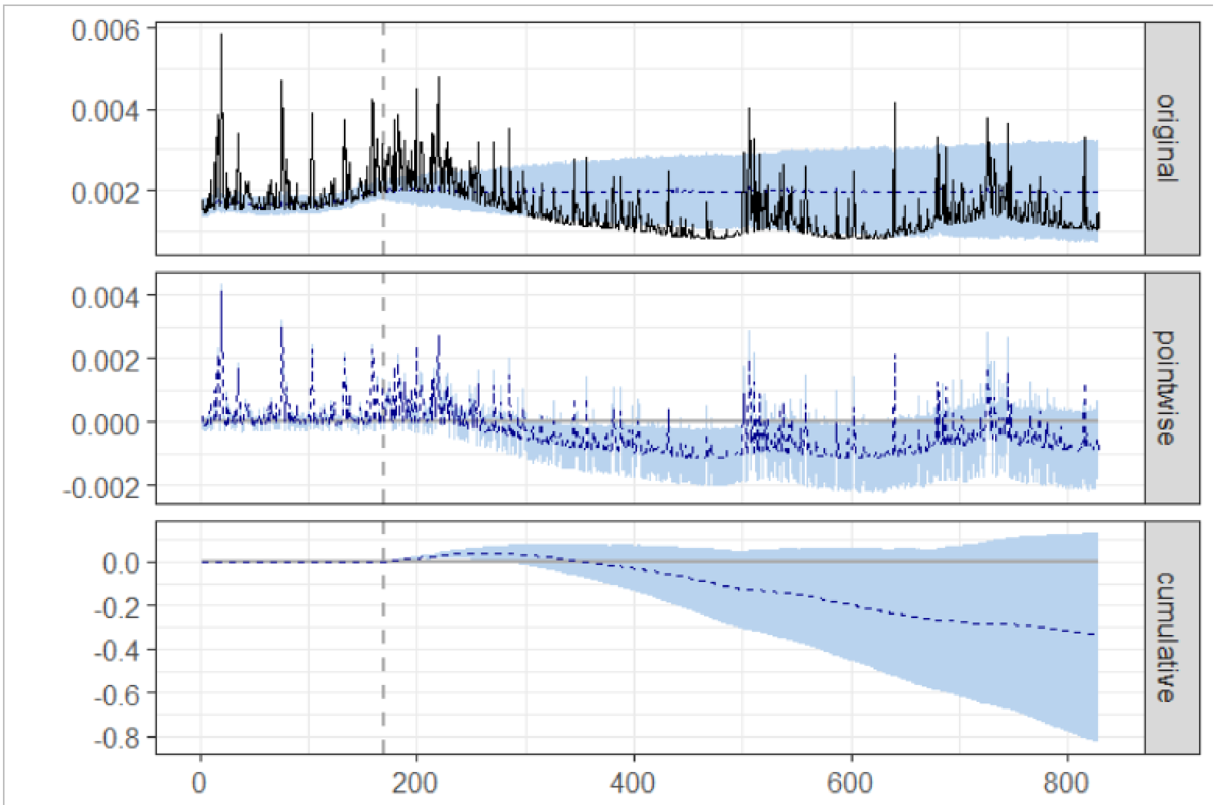


Figure 10: Inferring causal impact on USD Bitcoin spot market stochastic volatility with leverage, heavy tails and jumps through predictions, Bayesian Structural Time Series with student distribution. Two other markets (ETH and LTC, X1 and X2, respectively) were not subject to the intervention and thus are not included in the graph. A trajectory of a treated USD Bitcoin spot market stochastic volatility (Y) with an intervention on December 18th 2017. The difference between observed data of USD Bitcoin spot market stochastic volatility and predictions of this stochastic volatility is the inferred causal impact of the intervention. A cumulative impact of the introduction of Bitcoin futures on the Bitcoin USD spot market stochastic volatility (Posterior inferences, Eq. 22), for each day, the summed effect up to that day.

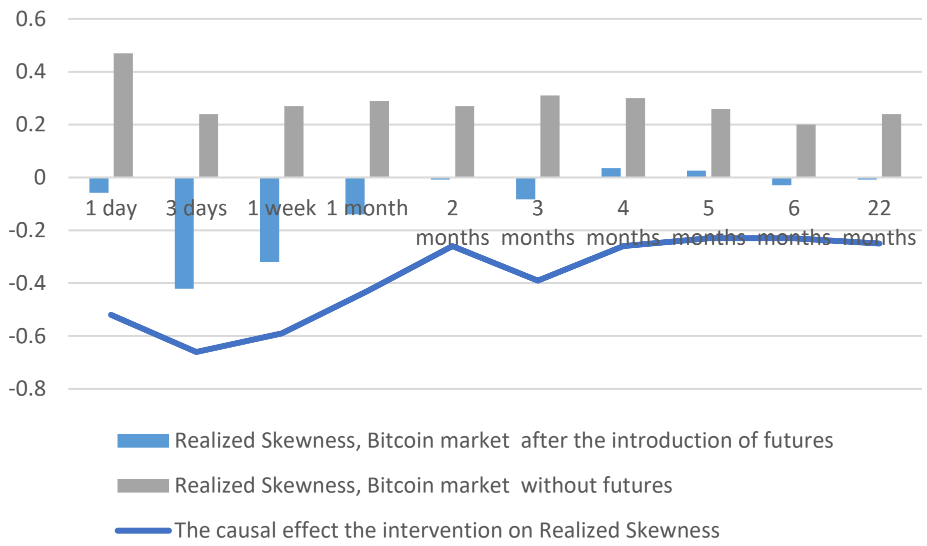


Figure 11: Dynamics of the realized skewness of the USD Bitcoin spot market return with and without the introduction of the Bitcoin futures (the y-axis values represent accumulative realized skewness of the Bitcoin spot market).

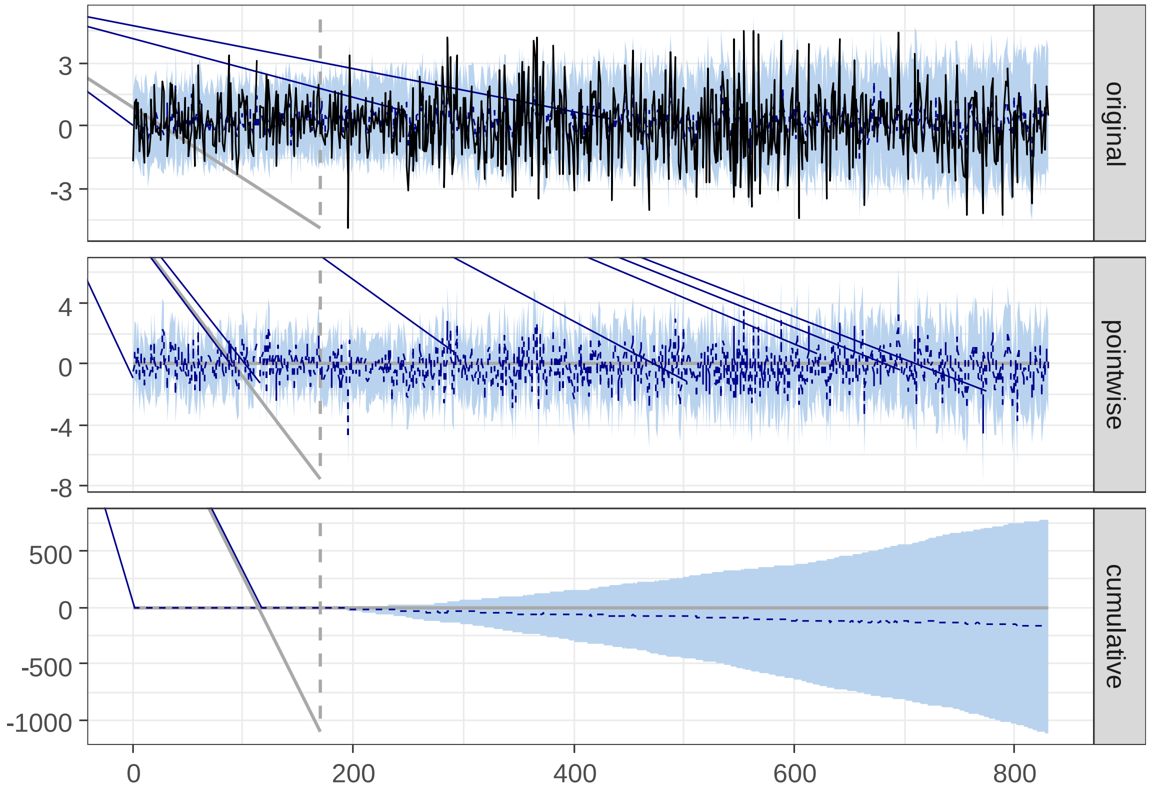


Figure 12: Inferring causal impact on USD Bitcoin spot market realized skewness through predictions, Bayesian Structural Time Series with student distribution. Two other markets (ETH and LTC, X1 and X2, respectively) were not subject to the intervention and thus are not included in the graph. A trajectory of a treated USD Bitcoin spot market realized skewness (Y) with an intervention on December 18th 2017. The difference between observed data of USD Bitcoin spot market realized skewness and predictions of this realized skewness is the inferred causal impact of the intervention. A cumulative impact of the introduction of Bitcoin futures on the Bitcoin USD spot market realized skewness (Posterior inferences, Eq. 22), for each day, the summed effect up to that day.

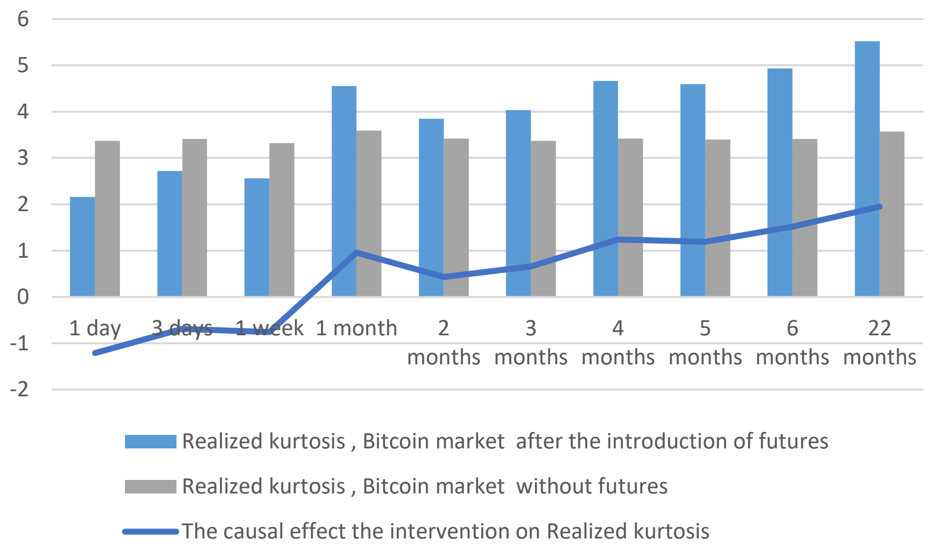


Figure 13: Dynamics of the realized kurtosis of the USD Bitcoin spot market return with and without the introduction of the Bitcoin futures (the y-axis values represent accumulative realized kurtosis of the Bitcoin spot market).

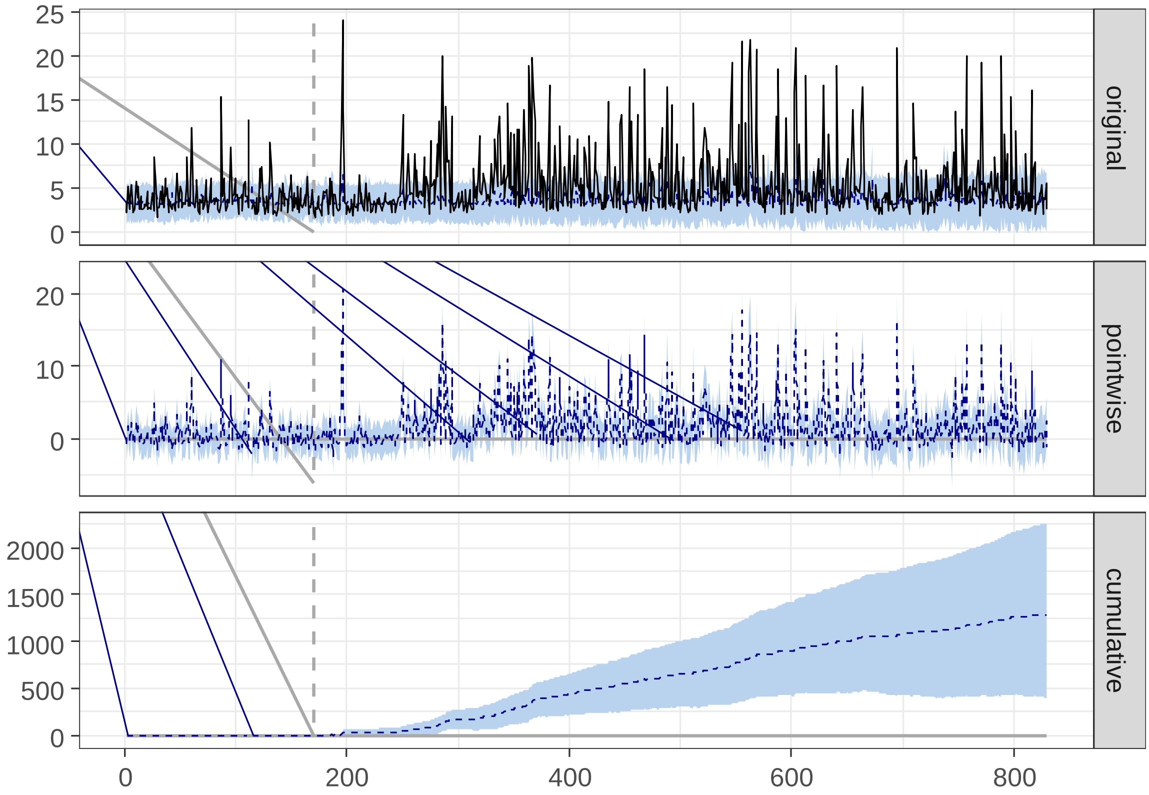


Figure 14: Inferring causal impact on USD Bitcoin spot market realized kurtosis through predictions, Bayesian Structural Time Series with student distribution. Two other markets (ETH and LTC, X1 and X2, respectively) were not subject to the intervention and thus are not included in the graph. A trajectory of a treated USD Bitcoin spot market realized kurtosis (Y) with an intervention on December 18th 2017. The difference between observed data of USD Bitcoin spot market realized kurtosis and predictions of this return is the inferred causal impact of the intervention. A cumulative impact of the introduction of Bitcoin futures on the Bitcoin USD spot market realized kurtosis (Posterior inferences, Eq. 22), for each day, the summed effect up to that day.

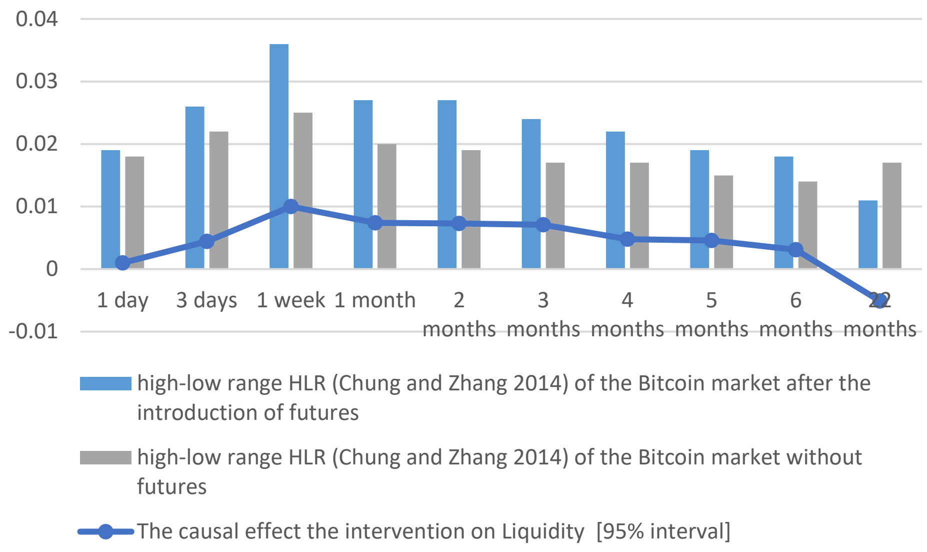


Figure 15: Dynamics of the high-low range HLR (Chung and Zhang 2014) of the USD Bitcoin spot market with and without the introduction of Bitcoin futures (the y-axis values represent the accumulative high-low range HLR of the Bitcoin spot market)

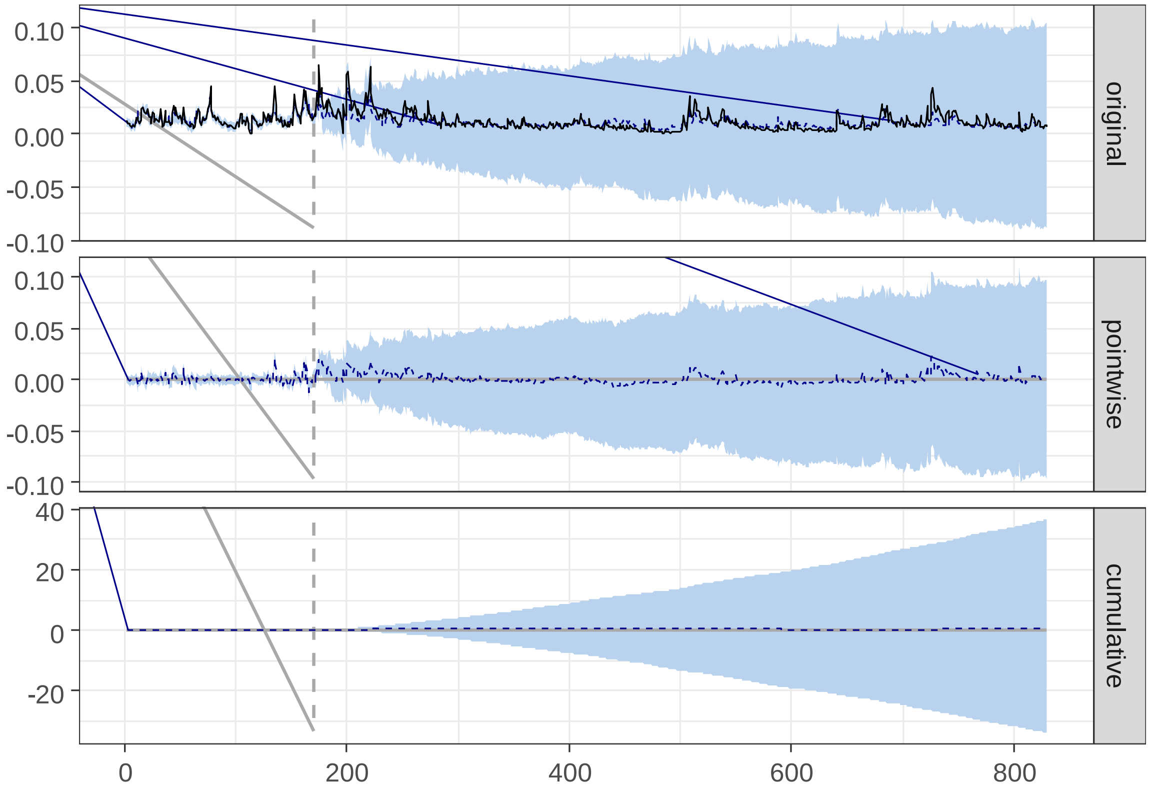


Figure 16: Inferring causal impact on USD Bitcoin spot market the high-low range, HLR, Chung and Zhang (2014) liquidity through predictions, Bayesian Structural Time Series with student distribution. Two other markets (ETH and LTC, X1 and X2, respectively) were not subject to the intervention and thus are not included in the graph. A trajectory of a treated USD Bitcoin spot market high-low range (Y) with an intervention on December 18th 2017. The difference between observed data of USD Bitcoin spot market high-low range and predictions of this high-low range is the inferred causal impact of the intervention. A cumulative impact of the introduction of Bitcoin futures on the Bitcoin USD spot market high-low range (Posterior inferences, Eq. 22), for each day, the summed effect up to that day.

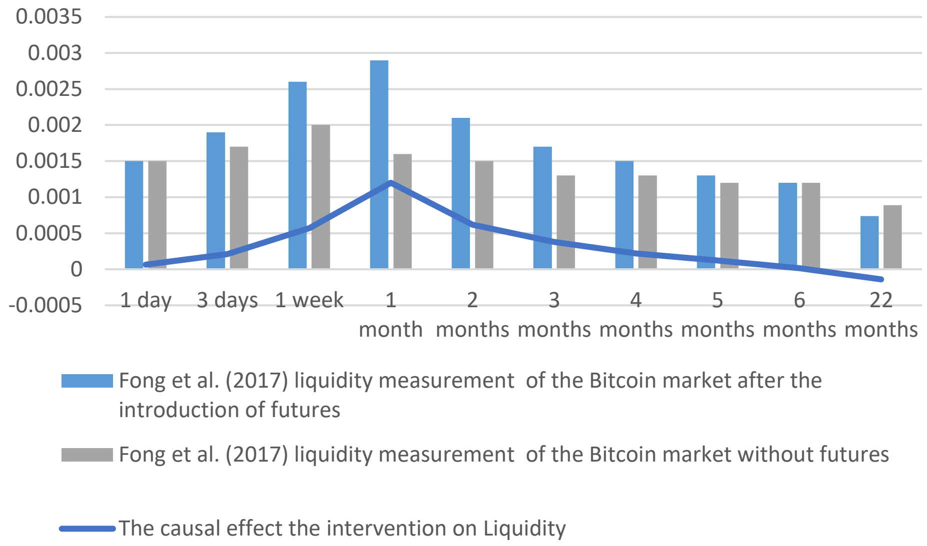


Figure 17: Dynamics of the VoV index (Fong et al. 2017) of the USD Bitcoin spot market with and without the introduction of Bitcoin futures (the y-axis values represent the accumulative VoV index of the Bitcoin spot market)

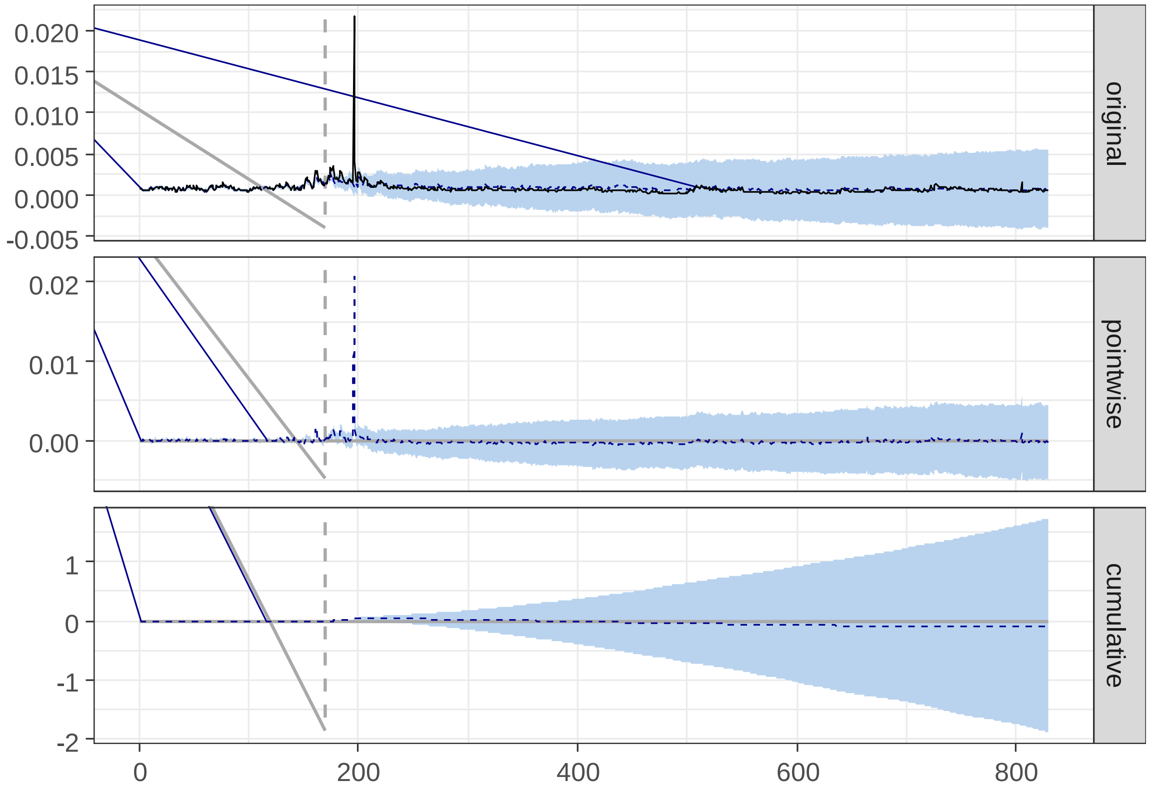


Figure 18: Inferring causal impact on the USD Bitcoin spot market VoV index, Fong et al (2017) liquidity through predictions, Bayesian Structural Time Series with student distribution. Two other markets (ETH and LTC, X1 and X2, respectively) were not subject to the intervention and thus are not included in the graph. A trajectory of a treated USD Bitcoin spot market VoV index (Y) with an intervention on December 18th 2017. The difference between observed data of USD Bitcoin spot market VoV index and predictions of this VoV index is the inferred causal impact of the intervention. A cumulative impact of the introduction of Bitcoin futures on the Bitcoin USD spot market VoV index (Posterior inferences, Eq. 22), for each day, the summed effect up to that day.