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Will Bitcoin ever become less volatile?

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ABSTRACT

We examine the drivers of Bitcoin volatility and discuss possible future developments, specifically what conditions need to be met for the volatility to decrease. Our instrumental variables analysis implies there needs to be a considerable inflow of small users into the system who are ideally not exchange traders and they do perform small transfers. Increasing exchange volume, on-chain transfers value, and Bitcoin price by themselves increase volatility of the cryptoasset.

1. Introduction

The early narrative of Bitcoin (Nakamoto, 2008) was the alternative to traditional money and fiat currencies. To meet the definition of money, Bitcoin (or any other candidate) needs to meet various criteria, one of them being stability or the so-called "store of value" characteristic (Bolton and Guidi-Bruscoli, 2021). The idea is simple – a person is willing to use an instrument as money if they are certain or find it very likely that, for a given amount, they will be able to purchase similar amount of goods and/or services at least in a medium term, or ideally in a long time horizon. A money-equivalent should thus not vary in its price or value much on a month-to-month or year-to-year basis, and similarly so on a day-to-day or even intra-day basis. In standard financial terms, such stability would translate into low volatility, or low price variability, as high volatility makes the holding risky and the future purchasing power unpredictable. A financial product with an ambition to become a global payment system or even a monetary system must be characteristic by low volatility. However, Bitcoin is historically known for its high volatility (Sapuric and Kokkinaki, 2014; Dyhrberg, 2016; Pichl and Kaizoji, 2017; Katsiampa, 2017; Baur et al., 2018). The traditional narrative stands in the line that Bitcoin will become more stable when its user base increases and it becomes more utilized in transactions. However, the past dynamics does not suggest that its volatility is in a downward trend (Baur and Dimpfl, 2021).

To illustrate the discrepancy between the standard fiat currencies in period between 1 January 2016 and 31 January 2022, we present Fig. 1, comparing the evolution of the Garman and Klass (1980)-based volatilities (more on the data selection later) of Bitcoin and three USD pairs – EUR, JPY, and GBP – and Table 1 provides some basic descriptive statistics for an easier comparison. Bitcoin shows much higher intra-day volatility than the three currencies, between five and seven fold as high. The volatility instability is even higher when these are compared, Bitcoin having around ten times as high standard deviation of its intra-day volatility. In this aspect, Bitcoin is much closer to the S&P500 stock index that is also shown in the figure and the table. When comparing volatility over the whole period, measured as the standard deviation of the daily open-close logarithmic returns, the differences are even more striking. While the sample standard deviation for Bitcoin reaches 0.0397, they are only 0.0002 for all three currencies. The standard

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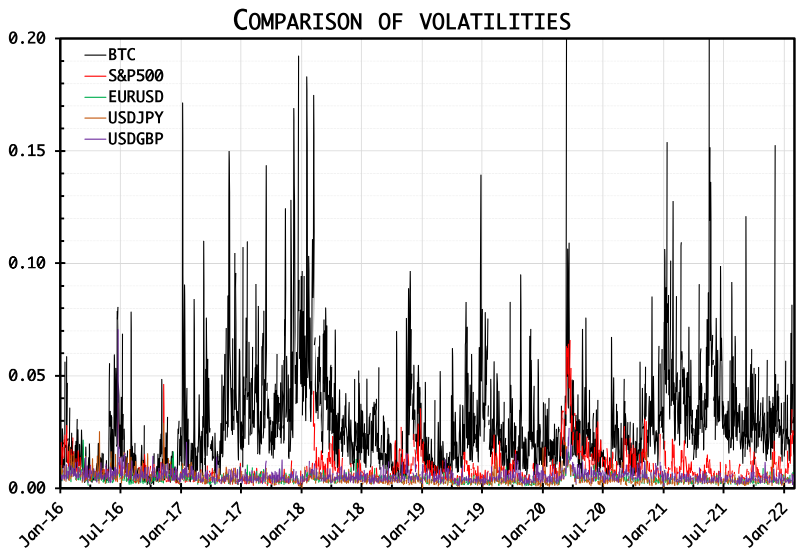

Fig. 1. Comparison of intra-day volatilities. Estimated using the (Garman and Klass, 1980) estimator.

Table 1
Comparison of Bitcoin and other volatilities. Means and standard deviations of the series in Fig. 1 in comparison to Bitcoin.

	mean	SD	mean vs 1/BTC	SD vs 1/BTC
BTC	0.0296	0.0253	–	–
S&P500	0.0083	0.0070	3.5426	3.6045
EURUSD	0.0042	0.0020	7.1135	12.3312
USDJPY	0.0043	0.0027	6.8905	9.3214
USDGBP	0.0053	0.0030	5.5487	8.3873

deviation of Bitcoin is thus approximately 200-times higher than the ones of the currencies, but only around three times higher than the one of the stock index with the standard deviation at 0.0116. The discussion about Bitcoin volatility decreasing markedly in time is thus essential for its ambitions towards serving as a money-equivalent. Here, we examine the factors that influence Bitcoin volatility, its dynamics and evolution, looking for possible scenarios that would lead to its suppression.

2. Methods and data

Bitcoin dynamics is driven by an interaction of speculative and fundamental components, even though the speculative components will not and even by definition cannot play a significant role in the long-term perspective. Still, a model explaining any of its aspects must take both into consideration. We propose the following model:

$$\begin{aligned}\log(\hat{\sigma}_t) = {} & \beta_0 + \beta_1 searches_t + \beta_2 \log(volumeBTC_t) + \\ & \beta_3 \log(transfersBTC_t) + \beta_4 \log(addresses_t) + \\ & \beta_5 \log(stables_t) + \beta_6 \log(price_t) + \beta_7 \log(\hat{\sigma}_{t-1}) + \varepsilon_t \end{aligned} \quad (1)$$

We aim to explain the values and dynamics of Bitcoin volatility. As an estimate of volatility σ, we utilize the Garman and Klass (1980) range-based estimator. The open-close-high-low prices are obtained from the CoinMarketCap website.[1] The construction of the model is based on the following logic. Investors' attention ($searches$) plays an important role in most structural models of Bitcoin price dynamics (Kristoufek, 2013; Garcia et al., 2014) and it will likely affect volatility as well. Higher attention means higher trading activity which might lead to higher volatility. From the other side, increased uncertainty can lead to higher interest in Bitcoin, hinting at possible endogeneity. The effect of trading activity on centralized exchanges ($volumeBTC$) on volatility is ambivalent. Low volume suggests low liquidity so that a large order can cause markable jump in price, increasing volatility. From the other side, high trading volumes can signify nervous trading activity and thus increased volatility. To make the things more complicated, increased uncertainty can lead to increased trading activity on the exchanges as the investors try to close their positions or their limit orders have already been cleared due to increased volatility, increasing the realized exchange volumes. The traded volume is thus likely endogenous. Similarly for the on-chain activity outside of the centralized exchanges ($transfersBTC$), increase of which might suggest increasing tension in the market as investors transfer their coins to the exchanges to take part in the market,

[1] https://www.coinmarketcap.com

likely increasing volatility. From the other side, increased uncertainty can lead to investors withdrawing their funds from exchanges and keeping them safe in their wallets. The on-chain activity is also proxied by the number of active addresses ($addresses$) with similar expectations and endogeneity issues as the previous two variables. The last from the possibly endogenous variables is the amount of stablecoins in circulation ($stables$). The fiat-backed stablecoins practically reflect the amount of fiat that has been injected into the ecosystem. For this reason, we do not include the cryptoassets-backed, algorithmic, or hybrid stablecoins. An influx of new capital to the system should lead to an increased trading activity. This is certainly not limited to Bitcoin only as new capital will likely be directed to other chains and decentralized finance applications. Still, such influx should affect Bitcoin market volatility as well. If the uncertainty is too high, the investors might fly back to fiat, burning stablecoins in exchange for fiat, thus lowering their circulating supply. The endogenous variables specifics are the following:

- $searches$ is the Google Trends[2] searches for "Bitcoin" and "BTC" (to obtain daily data from the Google Trends interface with a default monthly frequency, we download daily data for overlapping three-month periods and chain them, rescaling with respect to the overlapping month's mean search volume; each run forcefully resampled five times by adding a random alphanumerical string to the search term), weighted with respect to their average queries over the examined period;
- $volumeBTC$ is the overall exchanges traded volume in USD divided by the average daily price of Bitcoin, giving the exchanges traded volume in BTC, both the original volume in USD and the daily price was retrieved from the CoinMarketCap website;
- $transfersBTC$ is the overall on-chain transfers volume in BTC, it does not include the traded volume on the centralized exchanges, obtained from the Coinmetrics website[3] as $TxTfrValAdjNtv$;
- $addresses$ is the number of active addresses for the given day, obtained from Coinmetrics as $AdrActCnt$;
- $stables$ is the aggregate market capitalization of the largest fiat-backed stablecoins (USDT, USDC, BUSD, TUSD), obtained from CoinMarketCap

Bitcoin price ($price$) is included mainly for the narrative reasons as a regular argument around high volatility of Bitcoin is that it will get lower when the market capitalization becomes comparable with other asset classes. We thus include $price$ as an exogenous variable as the circulating supply (forming the market capitalization when multiplied by price) is one of the instrumental variables. We use the volume-weighted closing price from CoinMarketCap. The last right-hand side variable is the lagged volatility as volatility as well as most of the right-hand side variables are serially correlated. Controlling for the serial correlation by including the lagged dependent variable mitigates the issue of estimating the common stochastic trends rather than the actual effects.

As we expect $searches$, $volumeBTC$, $transfersBTC$, $addresses$, and $stables$ to be endogenous to $\hat{\sigma}$, we eventually estimate the model in Eq. (1) via the two-stage least squares (2SLS/TSLS, also instrumental variables, IV) procedure. For such, we need at least as many instrumental variables as there are right-hand side endogenous variables. Such variables should be highly correlated or explain a large portion of the dynamics of the right-hand side variables while remaining uncorrelated with the disturbances in Eq. (1). Selecting proper instruments is slightly easier for cryptoassets than for traditional assets. First, various cryptoassets have protocol-dictated characteristics that are thus strictly exogenous, i.e., they are not affected by any other variables. And second, the cryptomarkets do not influence the traditional financial markets but the vice versa relationship has emerged in the last few years. Traditional financial assets and indices can thus serve as good instruments. For the former group, we use the circulating supply of Bitcoin ($supply$) that is imprinted into the protocol, and the network hashrate that is a measure of security and amounts for the computing power provided to the network by validators/miners. For the latter group, we pick S&P500 index and gold as representatives of the traditional financial markets and Bitcoin competitors, and the VIX index as a measure of uncertainty on the traditional markets. Originally, the VIX index was included in Eq. (1) as the stock market uncertainty might spill over to the cryptomarkets but it turned out insignificant, thence it was moved to the instrumental side. The instrumental variables specifics are given below:

- $supply$ is the total amount of emitted bitcoins, obtained from Coinmetrics as $SplyCur$;
- $hashrate$ is the average amount of hashes being solved per second averaged over the given day, obtained from Coinmetrics as $HashRate$;
- $S\&P500$ is the closing price/value of the Standard & Poor's 500 index futures (E-Mini, nearest contract on CME), obtained from Yahoo Finance[4];
- $gold$ is the closing price of gold futures (nearest contract on COMEX), obtained from Yahoo Finance;
- VIX is the CBOE Volatility Index, obtained from Yahoo Finance

All exogenous variables, both included in Eq. (1) and excluded (instruments), are used in the first stage regressions on each endogenous variable. Fits from these regressions are then used instead of the original endogenous variables in the second stage of the estimation procedure (hence 2SLS). All variables but $searches$ are included in their logarithmic form due to different scaling as well as long right tail of the distribution (as documented in Table 2). The logarithmic form of the model specification also directs towards having exchange volume and on-chain transfers denominated in BTC rather than USD as the BTC price in USD is one of the included exogenous variables. As, e.g., the traded volume in USD is simply the traded volume in BTC multiplied by BTC price in USD, the estimated effects would be ambiguous. The analyzed period starts on 1 January 2016 and ends on 31 January 2022. As the traditional assets do not trade over the weekends and holidays, we assume their price constant over such days, not to lose observations and information on the cryptoasset's dynamics. Overall, there are 2223 daily observations.

[2] https://trends.google.com
[3] https://www.coinmetrics.io
[4] https://finance.yahoo.com

Table 2
Basic descriptive statistics.

	Mean	Median	Min.	Max.	SD	Skewness	Kurtosis	$q_{0.05}$	$q_{0.95}$
$\hat{\sigma}$	0.0283	0.0225	0.0016	0.2403	0.0240	2.6759	12.0560	0.0052	0.0722
searches	0.8073	0.6070	0.1336	11.4820	0.7981	5.4438	51.0180	0.1944	2.0405
volumeBTC (in M)	1.3351	0.7976	0.0566	13.1770	1.3677	2.0993	6.8402	0.1035	4.2188
transfersBTC (in M)	0.3211	0.2921	0.0743	1.0830	0.1360	0.8744	0.8251	0.1377	0.5732
addresses (in M)	0.7584	0.7293	0.3168	1.3665	0.2017	0.4366	−0.5475	0.46638	1.1329
stables (in B)	19.6240	2.6180	0.0010	144.7100	37.3190	2.0792	2.8720	0.0015	116.9700
price	13386	7451	366	67542	16699	1.6648	1.4829	444	54542
gold	1461	1326	1074	2052	253	0.5944	−1.2060	1193	1893
hashrate (in M)	64.2920	47.0340	0.6875	216.8600	58.0610	0.4882	−1.1146	1.2875	165.7700
S&P500	2969	2805	1825	4786	736	0.8363	−0.1778	2050	4481
supply (in M)	17.3780	17.4850	15.0330	18.9450	1.1126	−0.3078	−1.1404	15.4560	18.8430
VIX	17.9660	15.9600	9.1400	82.6900	8.1072	2.7280	12.0940	10.1100	31.8680

Table 3
First-stage regressions. Estimates are reported on the first lines, HAC standard errors MacKinnon and White (1985) in the parentheses on the second lines. The Wald/F-test is reported for the null hypothesis that parameters for all instrumental variables are zero.

	searches	$\log(volumeBTC)$	$\log(transfersBTC)$	$\log(addresses)$	$\log(stables)$
constant	42.0456	−233.8450***	−41.0385*	−43.6380***	−303.0520***
	(29.3328)	(44.7133)	(22.0811)	(15.6797)	(49.1805)
Instrumental variables					
$\log(supply)$	−2.3192	16.6516***	3.6214**	3.5914***	19.0158***
	(1.9004)	(2.9272)	(1.4300)	(1.0164)	(3.2235)
$\log(hashrate)$	−0.1100	0.6036***	−0.3445***	−0.1221***	0.4863***
	(0.0925)	(0.0867)	(0.0446)	(0.0315)	(0.1009)
$\log(S\&P500)$	−2.1130***	−5.5326***	−0.0219	−0.8392***	0.8848**
	(0.7856)	(0.3742)	(0.2526)	(0.1324)	(0.3761)
$\log(gold)$	1.4953***	0.9167**	−0.1110	0.6479***	−2.3005***
	(0.4918)	(0.3730)	(0.1682)	(0.1156)	(0.4118)
$\log(VIX)$	−0.2806*	−0.3871***	0.0694	−0.0976***	0.1066
	(0.1547)	(0.0950)	(0.0579)	(0.0272)	(0.0957)
Included exogenous variables					
$\log(price)$	0.7101***	−0.1103*	0.0571**	0.2000***	0.9755***
	(0.0865)	(0.0639)	(0.0279)	(0.0234)	(0.0734)
$\log(\hat{\sigma}_{-1})$	0.0298	0.2591***	0.1433***	0.0310***	0.800***
	(0.0412)	(0.0238)	(0.0119)	(0.0076)	(0.0271)
R^2	0.3338	0.8572	0.4596	0.6695	0.9847
$\bar{R}^2$	0.3317	0.8567	0.4579	0.6685	0.9846
Wald/F-test (IV)	17.269***	334.603***	39.223***	23.403***	171.077***

*, **, *** indicate significance at 90%, 95%, and 99% confidence level, respectively.

3. Results and discussion

We examine the driving forces of Bitcoin volatility within an endogenous system of variables. As we assume there are five right-hand side endogenous variables in Eq. (1), we start by presenting the first-stage regressions for them. In Table 3, we present the complete estimated models, splitting the instrumental variables and included exogenous variables. This helps us identify whether we have sufficiently good instruments (reasonable $\bar{R}^2$ of the regression) and whether all instruments are necessary (having instrumental variables statistically significant for at least one of the presumably endogenous variables). Both criteria are met. The lowest $\bar{R}^2$ is reported for the *searches* equation, yet still 0.33 is very reasonable for financial data at daily frequency. The amount of stablecoins in circulation is estimated almost precisely with $R^2 = 0.98$. From the instrumental variables, each is statistically significant for at least three endogenous variables, and jointly significant (Wald/F-test in the table), making them good fits. As the interpretation in the first stage of estimation is not essential for understanding the volatility dynamics, we move to the main results now.

Table 4 summarizes the final estimates. Before we get to the interpretation, let us note that the residuals of the model do not contain a unit root (Augmented Dickey–Fuller and Phillips–Perron tests), stationarity is not rejected (KPSS test), no autocorrelation is not rejected (Durbin–Watson test), there is heteroskedasticity (Breusch–Pagan test), and normality is not rejected (Jarque–Bera and Shapiro–Wilk tests). The tests results are available upon request. The results of the Hausman test for endogeneity of variables and Sargan's J-test for over-identification are shown in the table. The model is thus very well specified and valid. Due to heteroskedasticity, we present heteroskedasticity-consistent standard errors (MacKinnon and White, 1985). *searches* turns out to be insignificant in the model, all the remaining variables, both endogenous and exogenous, are statistically significant at the 99% confidence level. The lagged volatility is significant with the autoregressive coefficient estimated at 0.24 which is not too high to usurp the whole dynamics. The other, structural, variables play their important roles in the volatility dynamics. The number of

Table 4
Estimated model. Standard errors are HC according to MacKinnon and White (1985).

	estimate	SE	t-stat	p-value
$constant$	−13.2776	5.7033	−2.328	0.0200
$\log(addresses)$	−1.5042	0.4778	−3.148	0.0017
$\log(stables)$	−0.2282	0.0718	−3.178	0.0015
$\log(volumeBTC)$	0.4421	0.1008	4.386	$\ll 0.01$
$\log(transfersBTC)$	1.6923	0.5153	3.284	0.0010
$\log(price)$	0.9367	0.1605	5.836	$\ll 0.01$
$\log(\widehat{\sigma}_{-1})$	0.2388	0.0909	2.614	0.0090
R^2	0.5004			
$\bar{R}^2$	0.4881			
Hausman	288.114***			
Sargan	0.0350			

*, **, *** indicate significance at 90%, 95%, and 99% confidence level, respectively. Null hypothesis for the Hausman test states that both OLS and IV/2SLS estimates are consistent and OLS is efficient, alternative states that only IV/2SLS estimates are consistent. Sargan's test null hypothesis implies validity of over-identifying restrictions.

active users ($addresses$) lowers volatility. More active users thus push the volatility down. This is a good sign for the future of Bitcoin as a possible stable asset. Similarly, yet with a lower effect, for the amount of stablecoins in the system. The more fiat flowing into the system, the lower the volatility. However, the other two endogenous variables – $volumeBTC$ and $transfersBTC$ – increase volatility of Bitcoin. The higher traded volume on exchanges increases the volatility and the same is true for the on-chain transfers with the estimated elasticities of 0.44 and 1.69, respectively. The positive effect on volatility is also recorded for Bitcoin price with the estimated elasticity of 0.94. The fact that all these estimates are positive give a direct message that their increase in both USD and BTC terms has a boosting effect on volatility. And this is not completely desirable for the potential future dynamics. One would wish at least the transfers volume to play a positive role towards lowering Bitcoin volatility but it apparently does not. And the same is true for Bitcoin price which has a strong boosting effect on volatility.

Putting the results together, we have two counteracting forces — one formed by increasing the number of users and influx of fiat into the system that brings the volatility down, and the other formed by the exchange volume, transfers and price that lift the volatility up. This suggests that volatility can be pushed down if the number of active users and inflowing fiat overpower the increased trading and transferring activity as well as the price. As the effect of $addresses$ is much stronger than the one of $stables$, it points towards the need for many small users of the network that are not necessarily active traders. Still, it might be difficult to push back the effect of increased transfers out of these new active addresses. The new users thus need to be smaller in their transactions than the current average users and their transfers.

4. Conclusions

We have examined the drivers of Bitcoin volatility and discussed possible future developments, specifically what conditions need to be met for the volatility to decrease. Our instrumental variables analysis suggests that there needs to be a considerable inflow of small users into the network who are ideally not exchange traders and perform small transfers. Increasing exchange volume, on-chain transfers value, and Bitcoin price by themselves increase volatility of the cryptoasset. The presented analysis opens new avenues to future research into the driving forces behind Bitcoin, and cryptoassets in general, volatility as it shows that its dynamics is in fact driven by structural and fundamental sources within the system, not solely by external shocks.

CRediT authorship contribution statement

Ladislav Kristoufek: Conceptualization, Investigation, Methodology, Formal analysis, Writing – original draft, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

All data sources are open and referenced in the text.

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