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Do design features explain the volatility of cryptocurrencies?

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ABSTRACT

This paper examines the impact of cryptocurrency design features on their return volatility. We compile a sample of 58 cryptocurrencies, adopt the taxonomy of design features proposed by Eska et al. (2022), and estimate LASSO regressions. We document that older cryptocurrencies tend to be less volatile. Networks with mandatory transaction fees, cryptocurrencies based on (delegated) Proof-of-Stake, and those developed by private for-profit entities tend to be more volatile. Furthermore, we provide evidence that networks passing transaction fees and/or tips on to verifiers are associated with higher volatility levels.

1. Introduction

High volatility appears to be a general characteristic of cryptocurrencies. However, not all cryptocurrencies are equally volatile. Rather, as documented below, there are large cross-sectional differences. Understanding the determinants of these differences in return volatility is crucial for cryptocurrency investors, regulators, and developers alike. In this paper, we analyze whether differences in volatility can be traced back to differences in cryptocurrency design. If that were the case, investors could predict the volatility of a cryptocurrency based on its constellation of design features, and developers could deliberately design cryptocurrencies that can be expected to have low volatility. To conduct our analysis, we adopt the taxonomy proposed by Eska et al. (2022). These authors identify a wide variety of cryptocurrency design features and sort them into six categories, namely “development”, “technical”, “supply”, “transactions”, “usability”, and “general”. We collect a complete record of these design features for a broad sample of cryptocurrencies and then employ LASSO regressions to identify those design features that affect volatility.

Our paper contributes to the literature on cryptocurrency volatility. While numerous papers focus on the volatility of Bitcoin (e.g., Urquhart, 2017; Bystroem and Krygier, 2018; Conrad et al., 2018; Baur and Dimpfl, 2021; Ardia et al., 2019) or a limited number of other major cryptocurrencies, such as Ethereum or Ripple (e.g., Caporale and Zekokh, 2019; Chu et al., 2017; Cheikh et al., 2020; Gradojevic and Tsiakas, 2021), Panagiotidis et al. (2022) take a broader approach by analyzing a sample of 292 cryptocurrencies. They employ different GARCH-type models to examine regime changes in the volatility of these 292 cryptocurrencies. Other studies explore volatility dynamics across different cryptocurrencies and document spillover effects (e.g., Yi et al., 2018; Katsiampa et al., 2019; Aslanidis et al., 2021; Ji et al., 2019; Koutmos, 2018). Some further papers analyze factors and/or statistical models, as well as machine learning approaches, that can explain and predict cryptocurrency volatility (e.g., Baur and Dimpfl, 2018; Bouri

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et al., 2019; Katsiampa, 2019; Yen and Cheng, 2021; Catania and Grassi, 2022; D'Amato et al., 2022; Amirshahi and Lahmiri, 2023; Wang et al., 2023b). Notably, Wang et al. (2023a) consider sentiment and blockchain data such as the average block size and the hash rate as determinants of cryptocurrency volatility. These cryptocurrency-specific factors are the outcomes of the design and the economics of a cryptocurrency network. We extend this literature by adopting a perspective which relates cryptocurrency volatility to cryptocurrency design in the strict sense. To the best of our knowledge, our paper is the first to explore this relationship for a broad range of design features. The existence of a connection between design features and cryptocurrency valuation has been established by Hayes (2017) and Eska et al. (2022), both of which provide evidence that design features influence the market valuation of cryptocurrencies.

Our results are somewhat ambiguous because they partly depend on the volatility measure and the sample period. Nonetheless, several consistent findings emerge. In line with the theoretical model of Bolt and van Oordt (2020), we observe that older cryptocurrencies tend to be less volatile. Additionally, starting from 2020, our results demonstrate that cryptocurrencies which do not pass on any transaction fees/tips to agents maintaining the network's integrity exhibit lower volatility levels. Also, the presence of mandatory transaction fees increases the volatility of the corresponding coin. Besides, we reveal that, from 2020 until 2022, cryptocurrencies developed by private, for-profit entities are associated with higher volatility levels. For the years 2019 to 2022, we demonstrate that cryptocurrencies based on Proof-of-Stake (PoS) or delegated Proof-of-Stake (dPoS) are more volatile. Thus, we do not find convincing support for the prediction made by Saleh (2018), that Proof-of-Work (PoW) cryptocurrencies are inherently more volatile than those employing alternative consensus mechanisms.

The remainder of this paper is organized as follows. In Section 2 we describe our data and methodology, in Section 3 we present the results and Section 4 concludes.

2. Data and methodology

Cryptocurrencies exhibit a range of design features, often reflecting choices made by their developers. For instance, the consensus mechanism (PoW, PoS, etc.) is a key aspect. Other features, such as whether the developer is a for-profit organization, relate to the development process. Efforts have been made to categorize these design features (see, e.g., Garriga et al., 2020; Cousins et al., 2019; Eska et al., 2022). We adopt the taxonomy proposed by Eska et al. (2022), which is designed to explore the relationship between cryptocurrency design features and market valuation — a research question related to ours. Table 1 presents the six categories of design features, and lists the variables within each category and their respective definitions. Our data set includes design feature information, sourced from official network websites, white papers and other reliable sources, for a total of 58 cryptocurrencies.[1]

Besides data on design features, we obtain daily price data on the cryptocurrencies in our sample from the exchange APIs of eight different cryptocurrency trading venues, covering the period from January 2019 to December 2023. The selected trading venues are Binance, Bitfinex, Kraken, Bitstamp, Coinbase, Gemini, Bittrex, and Poloniex. According to Härdle et al. (2020), they are all considered reliable since they do not report inflated trading volumes. Our primary data sources are the respective exchange APIs, and in case of missing data, we first consult CryptoDataDownload, then CoinGecko, and if data is still unavailable, we resort to YahooFinance.

For our analysis, we consider two different sets of cryptocurrency returns: (i) Bitcoin (BTC) denominated returns and (ii) U.S. dollar (USD) denominated returns. For the BTC sample, we use daily closing prices (price of last trade before midnight UTC against BTC), aggregate the time series from these trading venues, and construct the volume-weighted average price from which we calculate the daily returns. We obtain daily returns on BTC prices for all cryptocurrencies in our sample — except BTC itself, obviously.[2] Sample (ii) is based on daily closing prices in USD quotation. On Binance, cryptocurrencies are traded only against EUR, so we convert EUR prices into USD using the daily USD-EUR exchange rate. Poloniex is excluded from our USD sample because it solely trades in Malaysian ringgit (RM). Eventually, we are left with a set of cryptocurrency prices against USD which is referred to as *direct prices*. Unfortunately, not all cryptocurrencies have direct prices against USD on the trading venues used for data sourcing. For instance, Bitfinex, the exchange with the most direct USD quotes, only lists direct quotes for 42 of the cryptocurrencies in our sample. Therefore, we convert BTC prices into USD prices using the USD-BTC exchange rate from the respective trading venues. We refer to these converted USD prices as *indirect prices*. We then compile our final *USD sample* as follows: (i) For cryptocurrencies quoted only in BTC on each trading venue, we use the indirect prices to calculate daily returns. (ii) For cryptocurrencies with both BTC and USD prices available, we calculate volume-weighted direct and indirect prices separately. Using these two price series, we then compute the volume-weighted average price and, eventually, the daily returns for these cryptocurrencies.

Both the BTC sample and the USD sample offer distinct advantages and disadvantages. The BTC sample generally avoids currency conversions but relies on transactions of one cryptocurrency against another (BTC). On the other hand, the USD sample measures prices against a fiat currency but includes indirect prices, which may raise concerns about arbitrage opportunities in cryptocurrency

[1] We initially collected data on design features for 79 cryptocurrencies, but not all features are available for every cryptocurrency, resulting in a reduced number of cryptocurrencies considered in our analysis. Ultimately, the final sample comprises 58 cryptocurrencies that have a sufficiently long time series for volatility calculation.

[2] Note that, if a cryptocurrency is traded against BTC on none of the eight exchanges in certain sample years, we rely on data from CoinGecko or YahooFinance. Neither CoinGecko nor YahooFinance provide BTC-denoted prices. Thus, we construct their BTC price by dividing their USD price by the USD price of BTC from CoinGecko.

Table 1
Design features: Variable description
This table describes the design feature variables, grouped according to the taxonomy developed in Eska et al. (2022).

Variable(s)	Binary	Description
Panel A: Development		
(1) DeveloperPublic (2) DeveloperNPO (3) DeveloperPrivate	yes (each)	Describes whether the development are conducted by (1) independent developers, (2) a non-profit organization, (3) a private, for-profit company
NoMajorityChanges	yes	Takes value of 1 if no part of the decision process about the networks' direction are passed on to the community
CodeNonPublic	yes	Describes whether the core code is fully accessible on Github or a similar platform
(1) CodeC++ (2) CodeGo (3) CodeOther	yes (each)	Primary language in which the core code is implemented is (1) C++, (2) Go, or (3) other
Fork	yes	Indicates whether a cryptocurrency network was forked from another one (take 1 as value) or built from scratch (take 0 as value)
Panel B: Technical		
Variable(s)	Binary	Description
(1) ConsensusPoW (2) ConsensusPoSdPoS (3) ConsensusOther	yes (each)	Type of consensus mechanism used by the network: (1) Proof-of-Work, (2) Proof-of-Stake or Delegated Proof-of-Stake, or (3) other
(1) HashSHA256 (2) HashEthash (3) HashScrypt (4) HashBlake (5) HashOther	yes (each)	Type of hash function used by the network to ensure transaction validity
HashAge	no	Age of the hash function used.
(1) CurveECDSA (2) CurveED25519 (3) CurveOther	yes (each)	Type of elliptic curve used in the respective network
Panel C: Supply		
Variable(s)	Binary	Description
NoMaxSupply	yes	Takes value of 1 if there is no limitation regarding the maximum number of coins to be issued
(1) FixedSupply (2) Deflationary (3) Inflationary (InflationaryDecreasing, InflationaryFixed, InflationaryFixedRate, InflationaryDynamic)	yes (each)	The cryptocurrency (1) have a fixed supply, (2) is deflationary, or (3) is inflationary with different supply growth schemes
RewardCoinbase	yes	Takes a value of 1 if each new entry to the ledger entails a specific number of new coins.
RewardInflation	yes	Takes the value of 1 if the distribution of new coins is not directly linked with coinbase rewards. Note that also a no reward structure is possible.
Panel D: Transactions		
Variable	Binary	Description
TheoreticalBlockTime (seconds)	no	Theoretically intended time between two ledger entries
BlockTimeAverage (seconds)	no	Average time between two ledger entries observed historically
BlocksizeLimit	yes	Takes the value of 1 when the network has a blocksize limit
TransactionFeeObligation	yes	Takes the value of 1 if the network has an obligatory fee for a transaction to be processed
NoTipSpecialTreatment	yes	Takes the value of 1 if the network does not allow their user to prioritize a transaction by paying a special fee (tip)
NoFeeTipForMinerForger	yes	Takes the value of 1 if the network does not (partly) pass transaction fees and/or tips to miners

(*continued on next page*)

Table 1 (*continued*).

Panel E: Usability		
Variable(s)	Binary	Description
(1) IntentionPayment (2) IntentionSmartContract (3) IntentionOther	yes (each)	Take the value of 1 when the network is intended to be (1) a payment system, (2) a smart contract platform, or (3) neither of the aforementioned, by the developers
SmartContractSupport	yes	Network support smarts contracts, *i.e.*, implicit smart contract possibility
TokenUsageBeyondPayment	yes	Services or rights beside the possibility to make financial transactions

Panel F: General		
Variable(s)	Binary	Description
LedgerOther	yes	Take the value of 1 when the network does not apply the blockchain technology but an alternative distributed open source protocol
AccountingBalance	yes	Accounting system is balance based, *i.e.*, the actual account balances are saved in blocks
(1) Anonymous (2) Pseudoanonymous (3) Non-anonymous	yes (each)	Describe the different privacy level of the network. Note that the Bitcoin network is identified as pseudoanonymous

markets.[3] To ensure robustness, we analyze both samples. The USD sample includes Bitcoin, whereas the BTC sample, with Bitcoin as the numeraire, does not. To validate consistency, we re-estimate all models for the USD sample excluding Bitcoin and find similar results.

We compute two volatility measures from the daily returns series: Interquartile range and standard deviation. These are calculated for five sample periods (each year from 2019 to 2023), including cryptocurrencies with at least 90 daily returns per year. Our design feature data is from Eska et al. (2022) and reflects the status as of September 2020. We are generally not capturing any time-series variation during the years 2021 to 2023. Even though certain networks undergo structural changes from time to time, these events are generally very rare. Thus, the impact of those on the results of our analysis is negligible.

Table 2 shows the descriptive statistics for our ten subsamples, *i.e.*, each combination of the BTC and USD sample with the five sample periods from 2019 to 2023. For each subsample, the table provides summary statistics for both volatility measures. The most important insight from the descriptive statistics is that the volatility of the cryptocurrencies in our sample varies considerably in the cross-section. It is this variation that we wish to explain in our empirical analysis. Additionally, the table highlights that volatility is generally higher in the BTC sample than in the USD sample.

In our empirical setup, we have a limited number of cross-sectional observations (cryptocurrencies) and numerous potentially relevant explanatory variables (design features). In a first step we reduce the number of explanatory variables by conflating some of the design feature variables.[4] Furthermore, instead of including the specific hash function employed by a cryptocurrency directly in our regression analysis, we capture its effect on volatility by considering its age. The majority of our independent variables are binary variables, with their default values corresponding to the design of the Bitcoin network. Furthermore, we redefine continuous variables such that the value for Bitcoin is zero. For example, we recalculate blocktimes as

$$BlockTime_{mod} = \frac{Blocktime_{Bitcoin} - Blocktime}{Blocktime_{Bitcoin}}.$$

We proceed in a similar way for the age of the hash function. Given this definition of our independent variables, all of them are zero for the Bitcoin network.

To assess the impact of cryptocurrency design on cryptocurrency volatility, we use LASSO (absolute shrinkage and selection operator) regressions, a widely-used technique in machine learning. This method is able to select those design variables that affect cryptocurrency volatility. Our LASSO regression approach connects variable selection and regularization by 10-fold cross validation, repeated 10,000 times in our analysis.[5]

3. Results and discussion

Table 3 shows the LASSO results for the interquartile range as volatility measure for the BTC and the USD sample. If a variable is never selected by the LASSO procedure, the respective cell in the table has no entry. For all variables selected at least once, we

[3] Indirect prices are a possible cause for concern because it is known that there are arbitrage opportunities in the cryptocurrency market (see, e.g., Makarov and Schoar, 2020). We note, though, that the trading venues in our sample belong to the most liquid market places for cryptocurrencies, and higher liquidity tends to be associated with higher price efficiency (see, e.g., Wei, 2018). For cryptocurrency-exchange pairs for which both direct and indirect prices are available, we find only very small price deviations.

[4] We conflate the variables *CodeGo* and *CodeOther* to a single binary variable *CodeNonC++* which is set to one if at least one of the former variables is one, and zero otherwise. Similarly, we introduce the binary variables *CodeNonECDSA*, *IntentionNonPayment* and *Inflationary*. We refer the reader to Eska et al. (2022) for further details.

[5] When we use five folds instead of ten in the cross-validation procedure our results remain qualitatively similar.

Table 2
Return data: Descriptive statistics
The table shows descriptive statistics (mean, quartiles, cross-sectional standard deviation) of the mean return, the standard deviation of daily returns and interquartile range of daily returns for each year of our investigation period.

Measure	BTC sample					USD sample				
	Mean	1st Quart.	Median	3rd Quart.	SD	Mean	1st Quart.	Median	3rd Quart.	SD
Panel A: 2019										
Mean Return	−0.0021	−0.0033	−0.0019	−0.0006	0.0028	−0.0000	−0.0008	0.0003	0.0020	0.0041
Standard Deviation	0.0489	0.0349	0.0419	0.0562	0.0204	0.0572	0.0458	0.0516	0.0602	0.0182
Interquartile Range	0.0429	0.0317	0.0379	0.0497	0.0158	0.0501	0.0417	0.0488	0.0547	0.0117
Panel B: 2020										
Mean Return	−0.0011	−0.0023	−0.0010	0.0002	0.0036	0.0039	0.0024	0.0038	0.0050	0.0030
Standard Deviation	0.0556	0.0410	0.0526	0.0625	0.0194	0.0656	0.0563	0.0634	0.0744	0.0138
Interquartile Range	0.0501	0.0361	0.0474	0.0575	0.0176	0.0592	0.0474	0.0564	0.0681	0.0162
Panel C: 2021										
Mean Return	0.0047	0.0024	0.0043	0.0060	0.0038	0.0070	0.0045	0.0064	0.0083	0.0039
Standard Deviation	0.0718	0.0603	0.0658	0.0782	0.0228	0.0849	0.0752	0.0804	0.0907	0.0233
Interquartile Range	0.0583	0.0495	0.0610	0.0664	0.0124	0.0762	0.0676	0.0782	0.0841	0.0132
Panel D: 2022										
Mean Return	−0.0012	−0.0023	−0.0008	0.0002	0.0030	−0.0030	−0.0041	−0.0029	−0.0020	0.0016
Standard Deviation	0.0425	0.0311	0.0382	0.0459	0.0170	0.0570	0.0478	0.0538	0.0618	0.0175
Interquartile Range	0.0344	0.0296	0.0331	0.0391	0.0073	0.0530	0.0480	0.0518	0.0584	0.0102
Panel E: 2023										
Mean Return	−0.0006	−0.0018	−0.0007	−0.0001	0.0017	0.0021	0.0009	0.0020	0.0028	0.0018
Standard Deviation	0.0397	0.0271	0.0347	0.0437	0.0181	0.0454	0.0353	0.0415	0.0536	0.0158
Interquartile Range	0.0312	0.0254	0.0308	0.0336	0.0088	0.0398	0.0345	0.0389	0.0452	0.0099

provide an estimate of the sign and strength of their impact on volatility. To accomplish this, we calculate the average value of the corresponding coefficient, incorporating a value of zero for cases where the variable was not selected. Furthermore, we report how frequently a variable has been selected by the LASSO regressions. Specifically, **** [***, **, *] indicates that the respective variable has been selected in more than 80% [60%, 40%, 20%] of the cases. We will focus our discussion on the design feature variables selected by the LASSO in more than 50% of the ten subsamples, representing the years 2019 through 2023, each denominated in either BTC or USD.

Five design features stand out for being selected in more than half of all subsamples, in some subsamples even in more than 80% of all LASSO regressions, and consistently exhibiting the same sign in all selected subsamples (light green in Table 3). First, among these features, age is the most noticeable, being selected in all subsamples: Older cryptocurrencies consistently exhibit lower volatility, aligning with studies by Bekaert and Harvey (1997) and Aggarwal et al. (1999) on traditional financial markets and Pessa et al. (2023) for the crypto universe.[6] Second, cryptocurrencies that do not pass transaction fees or tips onto verifiers are associated with lower volatility, a trend observed since 2020 with a significant spike in 2022. Although not selected in either 2023 sample, cryptocurrencies with mandatory transaction fees exhibit higher volatility levels, reflecting similar patterns observed in traditional financial markets (see, e.g., Umlauf, 1993; Jones and Seguin, 1997). Furthermore, from 2020 to 2022, cryptocurrencies developed by private, profit-driven teams consistently exhibit higher volatility. Lastly, cryptocurrencies employing PoS or dPoS consensus mechanisms show increased volatility, particularly evident in the BTC sample and during the early stages of the investigation period, contradicting Saleh (2018), who suggests Proof-of-Work cryptocurrencies are inherently more volatile.[7]

Two additional variables are selected in more than half of all cases, *FixedSupply* and *NoMajorityChanges* (light blue in Table 3). *FixedSupply* generally increases volatility, with an exception in the 2022 BTC sample where it has a negative sign, but its economic impact and selection frequency are low. The impact of an absence of opportunities for network members to participate in the governance process on volatility shows a temporal structure. While it exacerbates volatility in the early subsamples (2019 and 2020), it has a volatility-reducing effect from 2022 onwards.

When we analyze volatility using the standard deviation (results unreported) instead of the interquartile range, we consistently observe the same sign for the selected variables across subsamples (provided that the variable is selected for both measures). However, the results for the interquartile range show higher overall significance. This outcome is anticipated, as the interquartile range is a robust measure of volatility unaffected by outliers.

6 Pessa et al. (2023) state that large price variations are less likely with increasing cryptocurrency age. Other design features – in contrast to our paper – are not analyzed.

7 Another variable selected in more than half of the subsamples is *LedgerStyleOther*. The negative coefficient suggests that non-blockchain distributed ledger types decrease volatility. However, its economic impact and selection frequency are low, indicating minimal influence.

Table 3
Lasso results with interquartile range as dependent variable
This table reports the average of the parameter estimate, incorporating a value of zero for cases where the variable was not selected, indicating the economic significance from 10,000 LASSO regressions with the interquartile range of daily returns as the dependent variable and the design feature variables as the independent variables. Presented results in columns (1) to (5) base on the BTC sample whereas columns (6) to (10) consider the USD sample. Non-blank cells showing a figure without superscript belong to variables selected in less than 20% of the cases. Cells with "-" are associated with variables never selected.

	BTC sample					USD sample				
Variables	(1) 2019	(2) 2020	(3) 2021	(4) 2022	(5) 2023	(6) 2019	(7) 2020	(8) 2021	(9) 2022	(10) 2023
Constant	0.0423****	0.046****	0.0491****	0.0332****	0.0304****	0.0508****	0.0529****	0.0756****	0.052****	0.0412****
DaysAge	−0.0078****	−0.0004**	−0.0102****	−0.0009***	−0.0006*	−0.013****	−0.0059****	−0.0109****	−0.0123****	−0.0079****
DeveloperNPO	-	-	-	−0.0002	-	-	-	-	−0.0005****	-
DeveloperPrivate	-	0.0001*	0.0002**	0.0000	-	-	0.0012****	0.0008****	0.0022****	-
NoMajorityChanges	0.0013****	0.0000	-	−0.0000	−0.0000	-	0.0012**	-	−0.0008****	-
CodeNonPublic	-	0.0000	0.0000	-	-	-	-	-	-	-
CodeNonC	-	-	−0.0000	−0.0000	−0.0000	-	-	-	-	-
Fork	-	-	0.0013**	0.0001	0.0002*	-	-	0.0000	-	0.0001*
ConsensusPoSDPoS	0.005****	0.0013***	0.0037****	0.0008****	-	-	0.0000	-	0.0013****	-
ConsensusOther	−0.0000	-	-	−0.0001	-	-	-	0.0000	-	-
HashAge	-	-	0.0000	-	-	-	-	0.0000	-	-
CurveNonECDSA	-	0.0031****	−0.0000	0.0000	-	-	0.0069****	0.0000	-	-
NoMaxSupply	-	0.0000	0.004****	-	−0.0000	-	-	0.0003	-	−0.0000
Deflationary	-	-	0.0055****	−0.0000	-	-	-	0.0000	0.0000	-
FixedSupply	0.0000	-	0.0004**	−0.0000	0.0003*	0.0013****	-	0.0003	-	0.0019****
RewardCoinbase	-	-	−0.0011****	0.0000	-	-	-	−0.0003*	−0.0000	-
RewardInflation	0.0014****	-	0.0022****	-	0.0000	0.0059****	-	0.0016****	-	-
BlockTimeAverage	0.0000	-	0.0028****	0.0005	-	0.0001****	-	0.0003***	0.0053****	-
TransactionFeeObligation	0.0000	0.0000*	0.0019****	0.0001	-	0.0008****	0.0041****	0.0001*	-	-
NoTipSpecialTreatment	-	-	−0.0002**	−0.0002	−0.0000	-	-	−0.0000	-	-
NoFeeTipForMinerForger	-	−0.0000	−0.0021***	−0.0004	−0.0007****	-	−0.0003*	−0.0002	−0.0059****	−0.0011****
IntentionNonPayment	-	0.0025****	0.0034****	-	-	-	0.0017****	0.0023****	-	-
SmartContractSupport	-	-	0.0000	-	0.0000	-	-	-	-	-
TokenUsageBeyondPayment	-	-	-	-	0.0000	-	−0.0000	0.0000	-	-
LedgerStyleOther	−0.0000	−0.0000	−0.0012**	−0.0000	-	-	−0.0017*	-	-	−0.0000
AccountingBalance	-	-	−0.0000	−0.0001	−0.0000	-	-	-	-	-
Anonymous	-	-	0.0039****	0.0000	0.0000	0.0000	-	0.0011***	-	-
NonAnonymous	-	-	−0.0000	−0.0003	−0.0000	-	−0.0003*	-	−0.0003***	-
∅ Observations	48	57	57	57	57	49	58	58	58	58
∅ R^2	0.2012	0.1152	0.5061	0.0764	0.0318	0.3491	0.3078	0.2641	0.3940	0.1384

* Indicate that the respective variable is selected in at least 20% of the 10,000 LASSO regression.
** Indicate that the respective variable is selected in at least 40% of the 10,000 LASSO regression.
*** Indicate that the respective variable is selected in at least 60% of the 10,000 LASSO regression.
**** Indicate that the respective variable is selected in at least 80% of the 10,000 LASSO regression.

4. Conclusion

In this paper, we investigate whether the design features of cryptocurrencies affect their volatility. We utilize both BTC-denominated prices and USD-denominated prices to calculate daily returns. Conducted on a yearly basis, our analysis reveals that design features influence cryptocurrency volatility. While some design feature effects are limited to only one of the two volatility measure we use or only show up in some of the sample years, others exhibit consistent patterns. We show that older cryptocurrencies tend to be less volatile, which corresponds with their increased maturities and their more established network structures. A transaction fees/tip structure with direct transfers from transaction senders to verifiers increases the volatility of the respective cryptocurrencies. Additionally, cryptocurrencies implementing mandatory transaction fees and those developed by private teams exhibit higher volatility. Moreover, details of the consensus mechanism also affect the volatility of the respective cryptocurrencies. While this paper analyzes the impact of individual design features on volatility, it is conceivable that there are interdependencies between design features, and that specific combinations of design features drive volatility. Exploring such interdependencies is a promising avenue for future research.

CRediT authorship contribution statement

Fabian E. Eska: Writing – review & editing, Methodology, Formal analysis, Data curation. **Yanghua Shi:** Visualization, Formal analysis, Data curation. **Erik Theissen:** Writing – original draft, Project administration, Methodology, Conceptualization. **Marliese Uhrig-Homburg:** Writing – review & editing, Supervision, Project administration, Methodology, Conceptualization.

Data availability

The authors do not have permission to share data.

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