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ORIGINAL RESEARCH

Design and valuation of cryptocurrencies

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Abstract

We analyze whether the design of cryptocurrencies helps to explain the Huge cross-sectional variation in the market values of cryptocurrencies. We propose a taxonomy of design features and Hand-collect data on these features for a sample of 79 cryptocurrencies. Using a two-stage regression approach and LASSO regressions, we find, inter alia, that forks and deviations from the design of Bitcoin are associated with lower valuation. In contrast, non-anonymous cryptocurrencies and cryptocurrencies that do not pass on any transaction fees and/or tips to agents who maintain the integrity of the network have, on average, higher market values. These results are robust to variations in the way we measure market valuation.

Keywords Blockchains · Cryptocurrencies · Cryptocurrency design · Market valuation · LASSO

JEL Classification G1 · G2 · O30

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1 Introduction

Cryptocurrency values are highly volatile. While the time-series variation of cryptocurrency values in general, and that of Bitcoin in particular, attracts a lot of public attention, the cross-sectional differences in cryptocurrency values receive much less attention and are not well understood. Some cryptocurrencies, the so-called stablecoins, are backed by a portfolio of assets and thus have valuations linked to those assets, but most are not. The question therefore arises of what determines the relative valuations of different cryptocurrencies. This question is of obvious importance to users of and investors in cryptocurrencies, to trading venue operators and regulators.

The present paper sheds light on a specific aspect of this issue. We analyze empirically whether design features of cryptocurrencies and the specific characteristics associated with them affect their relative valuation. To this end, we first develop a taxonomy of the wide range of cryptocurrency design features and sort them into six groups, namely, (i) features related to the development process of the cryptocurrency, (ii) technical design features, (iii) features related to cryptocurrency supply, (iv) features related to transactions and transaction processing, and (v) features related to the usability of the underlying network as well as (vi) general features. Additionally, we include the age of each cryptocurrency to take into account the fact that older cryptocurrencies may have more users and, because of the network externalities associated with the number of users, may be more valuable. We Hand-collect a data set covering the design features and age of 79 cryptocurrencies with the highest market capitalization as of September 2020. Note that we only consider cryptocurrencies in the strict sense, i.e., coins, and exclude tokens because tokens do not operate on their own independent distributed ledger.[1]

We combine the data on design features with data on market capitalization, obtained by multiplying coin supply by coin prices. To take into account the overall market movements between the inception of a coin and our sample period, we additionally introduce and analyze a discounted version of market capitalization.

Our data set is characterized by a high number of potentially relevant independent variables relative to the number of cryptocurrencies in the sample. We use two methodological approaches to tackle this problem. First, we implement a two-stage cross-sectional regression approach inspired by Karnaukh et al. (2015). In step 1 we estimate six regressions in which we regress the market values of the cryptocurrencies in our sample on the design features contained in one of the six groups introduced above. In step 2 we estimate an encompassing regression in which we include those design features that have the highest explanatory power in the respective first-stage regression. Our second approach is the machine learning-based LASSO (least absolute shrinkage and selection operator) regression approach which combines variable selection and regularization. Our approach has two distinct characteristics which differentiate it from traditional asset pricing approaches. First, we explain the cross-section of market valuations, not the cross-section of returns. Second, we do not use a panel data set (or a repeated cross-section as in Fama and MacBeth (1973)) but rather a simple cross-section. This approach is warranted because our dependent variables (cryptocurrency market values) are highly persistent and most of our independent variables (the design features) have little or no time-series variation.

[1] Even though stablecoins have "coins" in their name, they are generally tokens operating on an existing distributed ledger and therefore are excluded from our analysis.

Our results indicate that cryptocurrencies with a Bitcoin-like combination of design features tend to have higher market capitalization than currencies that are distinctively different from Bitcoin. We also find that cryptocurrency networks that were spun off another network (so-called forks) and not built from scratch tend to have lower market capitalization, possibly because forks compete against their parent networks which are very similar and have a first-mover advantage. Cryptocurrencies that do not pass on any transaction fees and/or tips to agents who maintain the integrity of the network have, on average, a higher market capitalization. Such transaction fees can increase the fragility of the system: some users drop out directly, waiting times increase as a result, and consequently, even more users drop out (Easley et al. 2019; Huberman et al. 2021; Basu et al. 2023). Adverse effects related to network security are also conceivable (Pagnotta 2022). Our analysis also indicates that networks that require the disclosure of the real-world identities of their users have higher market capitalization. A possible reason for the higher valuation of non-anonymous currencies is that market participants price in the expectation of regulatory approval of non-anonymous currencies and/or regulatory action against anonymous currencies. Finally, we find (weak) evidence that currencies which had for-profit companies as their main developers have lower market capitalization, possibly because of a lower degree of decentralization.

Our paper contributes to the literature on the valuation of cryptocurrencies. A first strand of this literature addresses the question why cryptocurrencies which are neither backed by a pool of assets nor by a trustworthy institution such as a central bank have a non-zero value (Abadi and Brunnermeier 2018; Aoyagi and Adachi 2018; Biais et al. 2023; Bolt and van Oordt 2020; Dwyer 2015; Pagnotta 2022; Schilling and Uhlig 2019; Sockin and Xiong 2023; Zimmerman 2020). A second strand of the literature analyzes financial markets-related determinants of cryptocurrency values. Papers in this area analyze, for example, whether there are common factors driving cryptocurrency returns (Bianchi et al. 2022; Borri et al. 2022; Cai and Zhao 2024; Fieberg et al. 2024a; Han et al. 2024; Hu et al. 2019; Jung and Park 2024; Leong and Kwok 2023; Liu et al. 2020, 2022; Zhang et al. 2021), or whether macroeconomic or regulatory events affect cryptocurrency prices (Auer and Claessens 2021; Corbet et al. 2020; Koenraadt and Leung 2024; Li and Miu 2023). Some papers in this strand of the literature also include cryptocurrency-specific factors driven by network effects or cryptocurrency production costs (Bianchi and Babiak 2021; Bhambhwani et al. 2023; Cong et al. 2022; Fieberg et al. 2024b; Koutmos and Payne 2021; Liu and Tsyvinski 2021). The third strand of the literature, and the one most closely related to our paper, attempts to identify determinants of the cross-section of cryptocurrency values related to cryptocurrency design and blockchain functionality.[2] Two early papers that relate cryptocurrency design to price levels and returns are Hayes (2017) and Wang and Vergne (2017). Hayes (2017) investigates the impact of cryptocurrency design features on prices. He considers prices on a single day in 2014 and examines four design features, two of which (the rate of coin creation and the use of the scrypt algorithm) are found to be significant for price formation.[3] Wang and Vergne (2017), in contrast, analyze the returns of five cryptocurrencies and find that they are positively related to a measure of innovation potential as well as to supply growth and liquidity. Furthermore, Shams (2020) demonstrates that the comovement

[2] Mislavsky (2024) investigates the interplay between cryptocurrency design and consumer preferences, thereby stressing the importance of cryptocurrency design.

[3] Hayes (2017) also finds that the hashrate affects prices. The hashrate, however, is not a design feature of a cryptocurrency but rather a market outcome.

structure of cryptocurrencies is too high to be explained by similarities in characteristics such as the consensus mechanism. He suggests that trading on cryptocurrency exchanges is the main driver of the comovement. We extend this line of research by analyzing a data set much broader both in terms of cryptocurrencies and in terms of design features, by implementing two distinctively different empirical methodologies and various model specifications, and by proposing a novel taxonomy of cryptocurrency design features.

The remainder of this paper is structured as follows. In Section 2, we introduce our novel taxonomy of cryptocurrency design features, describe the data collection procedure, and present descriptive statistics on cryptocurrency design. In Section 3, we describe the methodology and in Section 4, we present and discuss the results of our empirical analysis. Section 5 concludes.

2 Cryptocurrency design features

In this section we introduce in Subsection 2.1 a novel taxonomy of cryptocurrency design features and hypothesize how the design features might affect the market value of a cryptocurrency. In Subsection 2.2 we describe how we collected data on the design features for a total of 79 cryptocurrencies and in Subsection 2.3 we present summary statistics.

2.1 Taxonomy

The different coins in the cryptocurrency universe can be characterized by combinations of various design features. While there exists a wide range of such features, these can be categorized into a small number of groups. The taxonomy we propose in this section differs from previous attempts which either do not allow a unique allocation of individual features to groups (Garriga et al. 2020), or which create abstract categories that are difficult to link to individual design features (Cousins et al. 2019). We propose six categories which are *Development*, *Technical*, *Supply*, *Transactions*, *Usability*, and *General*.

Development During the development process of a cryptocurrency a basic concept is transformed into implementable code. The identity of the developers and the organization of the process may affect the design and subsequent valuation of the cryptocurrency. With respect to the identity of the developers, we differentiate between (i) a loose network of independent developers and development teams (*DeveloperPublic*), (ii) a non-profit organization (NPO) (*DeveloperNPO*), or (iii) a private, for-profit company (*DeveloperPrivate*). It is not a priori clear how the identity of the development team will affect valuation. On the one hand, users may prefer a public development team because everyone can contribute to the development process, resulting in a high degree of decentralization, a particularly appealing cryptocurrencies characteristic. On the other hand, private developers may have a stronger incentive to make design choices that result in high valuation while public development teams may maximize welfare, which is not necessarily the same thing.

A closely related aspect is the question who decides on code changes. In some networks, a privileged group decides on code changes. In other networks, the decision whether a suggested modification is integrated into the core code is made by the network members and thus by majority voting. We define the dummy variable *NoMajorityChanges* which is set to 1 for the cryptocurrencies without such majority voting.[4] For those cryptocurrencies enabling majority voting the variable *NoMajorityChanges* is set to 0. We expect that users value decentralized decision making and that, consequently, cryptocurrencies without majority voting will be less valuable.

We also record general code-related features such as the core code's primary implementation language and the accessibility of the core code. With respect to the implementation language we differentiate between C++ (dummy variable *CodeC++*), Go (*CodeGo*), and other languages (*CodeOther*). With respect to accessibility we record whether the core code is fully accessible on Github or a similar platform. If this is the case, we set the dummy variable *CodeNonPublic* to 0; otherwise, it takes a value of 1. We expect that the lower transparency associated with a non-accessible implementation lowers market capitalization.

The last design feature in the category development is *Fork*, a dummy variable that indicates whether the initial implementation of a cryptocurrency network was forked from another network ($Fork = 1$) or built from scratch ($Fork = 0$). Forks often involve improvements to certain aspects of the parent network, which may potentially lead to a higher valuation of the fork. On the other hand, though, a fork is essentially a (modified) imitation of the parent which lacks innovation and has to overcome the first mover advantage of the parent network. Our prior expectation is that the second effect dominates the first, resulting in lower valuations of forks.

Technical The technical category comprises design features related to the consensus mechanism, the hash function, and the cryptographic methods used to authenticate signatures.

The consensus mechanism provides the rules for reaching agreement on the network status among its users and thus determines how transactions are validated. Validating a transaction is tantamount to authorizing a change to the distributed ledger that documents the change in ownership of the coins transacted. The first and most prominent consensus mechanism is "Proof-of-Work" (PoW), proposed by Nakamoto (2008).[5] The PoW mechanism results in extremely high energy consumption.[6] Currently, the most important alternative to PoW is "Proof-of-Stake" (PoS). PoS is based on the idea that agents with higher coin holdings are generally more interested in a healthy network. In line with this incentive, the probability that a network member can authorize a transaction is positively related to the coin holdings of that member. Besides (i) PoW and (ii) PoS, Irresberger et al. (2020) identify three further main consensus mechanisms: (iii) Hybrid PoW/PoS, (iv) Delegated Proof-of-Stake (dPoS), and (v) non-standard consensus mechanisms. We condense these five consensus mechanisms into three dummy variables for PoW (*ConsensusPoW*), for PoS and dPoS (*ConsensusPoSdPoS*), and for nonstandard mechanisms (*ConsensusOther*). We

[4] To assign a value of zero to *NoMajorityChanges*, we do not require that *all* decisions on code changes are made by the network members. Instead, we only require that some decisions are made in this manner.

[5] In PoW, consensus is reached through the work of so-called miners who compete to solve cryptographic puzzles.

[6] For instance, in 2022 the total electricity consumption of Bitcoin, the most prominent cryptocurrency based on PoW, summed up to about 107.65 TWh according to the Cambridge Bitcoin Electricity Consumption Index (see cbeci.org/) - a value roughly equal to the aggregated electricity consumption of the Netherlands (113 TWh in 2021) according to U.S. Energy Information Administration. Mora et al. (2018) argue that the carbon emissions caused by Bitcoin mining can push global warming above 2°C.

combine PoS and dPoS into one variable because both are based on the aforementioned idea that "richer" network members are more interested in the success of the network and should therefore have more influence on the validation process.[7] We capture hybrids between PoW and PoS by assigning the value of one to both *ConsensusPoW* and *ConsensusPoSdPoS*, for the respective cryptocurrencies. The lower energy consumption of PoS is a clear benefit and may result in higher valuation of cryptocurrencies adopting that mechanism. However, it is not clear that PoS and other alternative mechanisms are as resistant to attacks as PoW.[8] We therefore have no clear prediction on the sign of the coefficients for the three consensus mechanism dummy variables.

Transactions are combined into blocks, and hash functions are used to ensure that blocks cannot be changed ex-post.[9] Within the cryptocurrency universe, many different hash functions are used for this purpose. For our data set on design features, we categorize them in to five different specifications: (i) SHA-256, the function which Bitcoin uses, (ii) Ethash or the closely related keccak256 function, (iii) blake, (iv) scrypt,[10] and (v) other hash functions. While we do collect the corresponding data for all cryptocurrencies in our sample, we do not want to inflate the number of independent variables in our empirical analysis. Therefore, we introduce the age of the hash function as a proxy for the quality of the hash function. More recently developed hash functions will typically offer a higher level of security.[11] Consequently, we anticipate that the age of the hash function will negatively affect market valuation.

Cryptocurrencies use Digital Signature Algorithms (DSA) which are based on elliptic curve cryptography in order to authenticate the signatures of the parties in a transaction. We differentiate between three types of elliptic curves, (i) ECDSA, the curve which is used, among others, by the Bitcoin network, (ii) Ed25519, a widely used alternative,[12] and (iii) other curves. While the DSAs are essential for secure coin transfer, not many network users are aware of the specific differences between the elliptic curves. We therefore do not expect a significant impact on market values.

Supply The process of supplying cryptocurrencies is very different from the process of supplying fiat currency. While the supply of fiat currency depends on the monetary policy of the respective central bank and is therefore subject to discretionary decisions, the supply of cryptocurrencies is predetermined in most networks. Oftentimes, the growth in coin supply is linked to the process of verifying transactions – agents who successfully participate in the verification process are rewarded with newly created coins. In addition, many cryptocurrencies have a supply cap, implying that the maximum number of coins cannot exceed

[7] The difference between PoS and dPoS is the fact that in dPoS the network member can outsource the task to third parties, so-called delegates.

[8] As a case in point, before the Ethereum network eventually adopted PoS in September 2022, it was stated on the Ethereum homepage that "[PoS] is still in its infancy, and less battle-tested, compared to [PoW]" (see ethereum.org/en/developers/docs/consensus-mechanisms/pos/).

[9] Each block contains the hash value of the previous block. If a block is changed, its hash value will also change and will then deviate from the value written in the next block. This link between blocks makes ex-post changes to a block easily detectable.

[10] For PoW-based crpytocurrencies, Hayes (2017) finds a positive influence of scrypt on prices.

[11] See e.g., Pfautsch et al. (2020) or https://www.streetdirectory.com/etoday/-ejcluw.html.

[12] For instance, Lisk, Monero and Zcash use this elliptic curve for the authentification of signatures. Ed25519 offers a higher level of anonymity compared to ECDSA.

a predetermined threshold. We use the binary variable *NoMaxSupply*, set to 1 in case of no cap, indicating the non-existence of a predetermined maximum number of coins.

In general, cryptocurrencies can (i) have a fixed supply (a feature captured by the dummy variable *FixedSupply*), (ii) be deflationary (*Deflationary*), or (iii) be inflationary. If the supply is fixed, the number of coins in circulation does not vary over time. For deflationary currencies, the number of coins decreases over time as a result of certain “burn mechanisms”. Inflationary currencies come in various forms, characterized by different supply growth schemes. Many cryptocurrencies with increasing supply have a reward reduction scheme similar to that of Bitcoin in place. Consequently, the supply curve is increasing and concave over time, and possibly converges to a predetermined threshold. The dummy variable *InflationaryDecreasing* identifies currencies with that feature. Instead of a reward reduction scheme, cryptocurrencies may have constant rewards, resulting in a linear supply function over time (*InflationaryFixed*). Finally, the supply curve may be convex. This can be achieved by fixing the supply growth rate (rather than the number of coins issued per unit of time). The growth rate is often referred to as the rate of inflation of the currency (*InflationaryFixedInflationRate*). Finally, some currencies have dynamic and thus time-varying supply growth rates, resulting in non-deterministic supply growth (*InflationaryDynamic*). We expect that cryptocurrencies with supply caps, fixed supply and deflationary currencies have lower value because the supply restrictions may limit the adoption of the currency by users.

As noted, the reward to those agents verifying transactions in the network is linked to coin supply. The reward can be a coinbase reward (the creator of each new entry to the ledger earns a specific number of new coins) or an alternative reward distributions scheme based on inflationary schemes, e.g., one where rewards are distributed among a larger network user group (e.g., all verifiers) and are not necessarily attached to individual new ledger entries. We capture these two cases by the dummy variables *RewardCoinbase* and *RewardInflation*. In either case, those two reward distribution schemes incentivize agents to contribute to a healthy network and thus, we expect a positive influence on market capitalization.

Transactions The category transactions contains design features related to transactions on the cryptocurrency network and the ways in which these transactions are processed.

The number of transactions a network can process per period of time is often referred to as the throughput. In theory it can be measured by transactions per second (TPS). However, TPS is controversial, primarily due to the inconstistency in its measurement across different networks. Therefore, we proxy TPS by the time between neighbouring blocks and the existence or non-existence of a blocksize limit. The time between blocks determines the frequency of changes of the distributed ledger. We differentiate between the theoretically intended minimum time between two blocks (*TheoreticalBlockTime*) and the actually observed time between blocks (*BlockTimeAverage*).[13] We note that shorter time between blocks does not only mean that more transactions can be processed per unit of time, but also means that the minimum time it takes to complete a transaction is lower. We therefore expect that shorter time between blocks is associated with higher valuation. A blocksize

[13] If there was a fork within a network that induced a change in at least one of these variables, we record the post-fork values of the variables. In the subsequent analysis, we restrict ourselves to the actually observed blocktime due to data availability and reliability.

limit sets a limit to the number of transactions that can be processed per unit of time and thus limits the throughput of the network. The dummy variable *BlocksizeLimit* is set to 1 if such a limit exists.[14] We expect that the existence of a blocksize limit affects market value negatively.[15]

In many cryptocurrency networks users have to pay a fee for the processing of their transactions. We include three variables that intend to capture the existence and design of such fees, *TransactionFeeObligation*, *NoTipSpecialTreatment*, and *NoFeeTipForMinerForger*. *TransactionFeeObligation* records whether a cryptocurrency network has a mandatory fee for a transaction to be processed. Because the existence of a mandatory fee makes it more expensive to use the network, we expect a negative impact on market valuation. Some networks allow their users to prioritize a transaction by paying a special fee, often called tip. We define the dummy variable *NoTipSpecialTreatment* which is set to 0 (1) if such tips are (not) possible. We expect that investors value the possibility to prioritize their transactions and therefore expect a positive impact on market valuation. The third variable, *NoFeeTipForMinerForger*, is set to 1 for networks where the transaction fees and/or the tips are not – neither fully nor partly – passed on to the agents verifying transactions (e.g., miners in PoW and stakers in PoS). A scheme where fees and/or tips are passed on to those agents (miners or stakers) makes their activities more profitable and may thus attract more agents. This, in turn, increases the degree of network decentralization and the security (i.e., resistance against attacks) of the network. We therefore expect a negative effect of *NoFeeTipForMinerForger* on market values.

Usability The first cryptocurrency, Bitcoin, was devised as a means of payment. However, there are use cases for cryptocurrencies beyond that. A cryptocurrency network can be a payment system, a platform for smart contracts (the Ethereum network is a case in point), or it can serve other purposes such as decentralized finance applications. We capture the intended use of a cryptocurrency by three dummy variables, *IntentionPayment*, *IntentionSmartContract*, and *IntentionOther*. We expect that cryptocurrencies that serve purposes beyond being a means of payment have higher market values.

In some networks the ownership of coins embodies rights (e.g., voting rights), or possibilities of usage beyond making payments. The variable *UsageBeyondPayment* takes on the value one for cryptocurrencies for which this is the case. We expect a positive coefficient. Some cryptocurrency networks offer implicit smart contract support (without requiring sidechains or similar arrangements).[16] For networks with this feature we set the dummy variable *SmartContractSupport* to one. We anticipate a positive value impact due to expanded functionalities, but the risk of hacking attacks on smart contracts resulting from implementation errors is likely to introduce a negative effect. The net effect remains undetermined.

[14] We were unable to verify whether a blocksize limit exists for some cryptocurrencies, implying that we have missing data for this variable.

[15] We note, though, that an unlimited block size may result in excessively large ledger entries.

[16] There certainly are other features that extend the usability of a cryptocurrency. However, we are not aware of other features that are consistently documented in the public domain. We therefore restrict ourselves to the variable *SmartContractSupport*.

General The final category comprises three further design characteristics that may potentially affect valuation. Most cryptocurrencies bundle transactions into blocks and update the network status by appending blocks to a blockchain. Since Ripple's introduction in 2012, the cryptocurrency space has expanded to include networks that utilize alternative distributed open-source protocols instead of blockchain technology. The variable *LedgerOther* identifies such networks. Generally, these alternative designs aim at overcoming the scalability problem of blockchains, thereby potentially creating possibilities for new usages of cryptocurrencies. This aspect might lead to a higher valuation of the respective cryptocurrencies. However, these no-blockchain designs may be less secure (or less "battle-proof"), limiting their adoption and lowering their valuation. As it is unclear which of these effects is stronger, we do not have a clear prediction for the sign of the coefficient on the *LedgerOther* variable.

There are two accounting schemes that are commonly applied in the cryptocurrency world. The first cryptocurrencies (including Bitcoin) relied on unspent transaction outputs (UTXOs) to balance the ledger. Under this accounting scheme the ledger does not store information on account balances. Consequently, to infer account balances one has to process the entire blockchain and sum up all UTXOs logged to the respective account. Given the enormous size of many blockchains this may not be the most efficient solution. Therefore, other cryptocurrency networks apply a traditional balance accounting scheme. Such networks store every account's balance on the blockchain (similar to banks that store customer account balances using electronic records). This accounting scheme does not require a network member to parse the whole ledger to infer account balances. Rather, a synchronization without accessing the whole history of the ledger becomes possible. We identify cryptocurrencies using such an accounting scheme by the variable *AccountingBalance*. We expect a positive coefficient because of the efficiency and intuitive appeal of these accounting schemes.

Another important feature is the degree of anonymity that a cryptocurrency network offers its users. In networks like Bitcoin, every transaction and wallet balance can be traced back to a pseudonymous public address. Other networks prioritize providing enhanced privacy and facilitate fully anonymous transactions through specific cryptographic methods.[17] We identify networks that allow anonymous transactions by the variable *Anonymous*. Enhanced privacy meets the demand for censorship resistance[18] and thus makes anonymous cryptocurrency networks more attractive. We therefore expect that networks supporting full anonymity have higher valuation than those which only allow pseudonymous transactions. On the other end of the anonymity spectrum are cryptocurrency networks that connect the addresses and transactions to real world identities (identified by the variable *NonAnony-*

[17] Examples include zk-SNARKs (Zero-Knowledge Succinct Non-Interactive Argument of Knowledge) of Zcash, a form of zero-knowledge cryptography. In this network, transactions can be fully encrypted but the validity can still be verified with specific zk-SNARK proofs. In detail, a "prover" can prove to a "verifier" that a statement is true without revealing any information beyond the validity itself. Via specific combinations, this procedure allows transaction processing without disclosing information about the transaction itself.

[18] Pagnotta and Buraschi (2018) state that censorship resistance "has multiple sources including financial repression through governmental capital controls; option-like hedging against government abuses such as arbitrary wealth confiscations or the targeting of political dissidents and/or religious groups; hedging against changes in inheritance laws; the risk of disruptions of the traditional banking system due to bank runs, fiat hyperinflation or forced maturity conversion of bank deposits; the ability to secure wealth transfers in the event of armed conflicts, territorial invasions, civil wars, refugee crises", as well as criminal activity.

mous). Such a non-anonymous design may offer advantages with respect to regulatory acceptance because KYC (Know-Your-Customer) is already fulfilled. Supervisory authorities might thus favor non-anonymous cryptocurrencies.

In the first columns of Table 1 we list the variables introduced above, specify whether they are binary or not, and indicate the coefficient signs ("+" or "-") we expect based on the prior discussion. A "0" indicates that we either have no clear prediction for the respective variable, or that we consider its impact on valuation to be negligible.

2.2 Data collection

Unlike price and quotation data for cryptocurrencies, data on design features cannot be obtained from data vendors. We therefore had to hand-collect data on the variables introduced in Section 2.1. We primarily used data sources directly related to the network founders, the development team, and the network community, such as whitepapers, official network websites, developers' documentation, and the code repository. When necessary information was not available from these sources, or when it was incomplete or inconsistent, we extended our search to expert forums like the respective subreddits and those on the developers' portals.[19] For the variables *IntentionPayment*, *IntentionSmartContract* and *IntentionOther*, we restricted our data collection procedure to the tags provided by Coinmarketcap and Messari. For well-known and highly capitalized cryptocurrencies we could collect the required data rather easily. However, the quality of documentation is often poor for less well known and less capitalized cryptocurrencies. For many of these currencies the data required for our analysis was unavailable, despite accessing a broad range of different data sources. Eventually we managed to collect data on the relevant design features for the 79 cryptocurrencies with the highest market capitalization as of September 2020.[20] We admit that our data set is not free from survivorship bias. However, because data on design features of cryptocurrencies with low market valuations and of cryptocurrencies that were discontinued is unavailable, there is no straightforward way to resolve this problem. As explained below, we try to mitigate this by focusing our main analysis on the market valuation of the cryptocurrencies in the quarter following sample construction.

When we include in our data set soft forks that imply a change in at least one design features of our taxonomy,[21] our data set increases from 79 to 114 observations. Note, though, that this all-time data set includes those cryptocurrencies twice that experienced a design change that was not associated with a hard fork. These two versions of the same cryptocurrency existed in different periods; i.e., at each point in time only one of them existed. The all-time data set allows reconstruction of the exact design configuration of all cryptocurren-

[19] Whenever relying on these data sources, we ensured that the information in our data set was backed by two independent sources.

[20] We have checked the correlations between the design feature variables. Most correlations are below 0.2, the largest individual value in the sample is 0.43 (correlation between the variables "NoFeeTipForMinerForger" and "LedgerStyleOther"). We therefore conclude that multicolinearity is not an issue.

[21] For instance, Monero, a cryptocurrency which allows completely anonymous transactions by obscuring transaction senders and recipients through cryptography, originally had a blocktime of one minute. In 2016, the blocktime was raised to two minutes (alongside with some other changes not relevant in the context of our design feature variables). Such a situation implies two entries in our all-time data set. The first one includes the initial blocktime of one minute while the blocktime variable is set to two minutes in the second entry. Such changes are not necessarily associated with hard forks that result in two cryptocurrencies existing simultaneously after the fork date.

Table 1 Design features variables, expected influence, and descriptive statistics

Variable	Binary	Predicted influence	As of December 2020			All-time		
			Obs.	Mean	Std. Dev.	Obs.	Mean.	Std. Dev.
Panel A: Development								
DeveloperPublic	yes	+	79	0.2025	0.4045	114	0.2368	0.4270
DeveloperNPO	yes	+	79	0.2785	0.4511	114	0.2544	0.4374
DeveloperPrivate	yes	−	79	0.5190	0.5028	114	0.5088	0.5021
NoMajorityChanges	yes	+	79	0.3544	0.4814	114	0.3158	0.4669
CodeNonPublic	yes	-	79	0.0380	0.1924	114	0.0263	0.1608
CodeC++	yes	0	79	0.3924	0.4914	114	0.4386	0.4984
CodeGo	yes	0	79	0.3671	0.4851	114	0.3246	0.4703
CodeOther	yes	0	79	0.2532	0.4375	114	0.2456	0.4324
Fork	yes	−	79	0.5063	0.5032	114	0.5526	0.4994
Panel B: Technical								
ConsensusPoW	yes	0	79	0.3165	0.4681	114	0.4386	0.4984
ConsensusPoSdPoS	yes	0	79	0.4937	0.5032	114	0.4035	0.4928
ConsensusOther	yes	0	79	0.2278	0.4221	114	0.2018	0.4031
HashSHA256	yes	N/A	79	0.4304	0.4983	114	0.4035	0.4928
HashEthash	yes	N/A	79	0.1519	0.3612	114	0.1316	0.3395
HashScrypt	yes	N/A	79	0.0759	0.2666	114	0.0789	0.2708
HashBlake	yes	N/A	79	0.1392	0.3484	114	0.1140	0.3193
HashOther	yes	N/A	79	0.2785	0.4511	114	0.3421	0.4765
HashAge	no	–	79	4752.99	1993.83	114	4614.67	1994.05
CurveECDSA	yes	0	79	0.6329	0.4851	114	0.6316	0.4845
CurveED25519	yes	0	79	0.3418	0.4773	114	0.3158	0.4669
CurveOther	yes	0	79	0.0759	0.2666	114	0.0877	0.2841
Panel C: Supply								
NoMaxSupply	yes	−	79	0.3418	0.4773	114	0.2895	0.4555
FixedSupply	yes	−	79	0.2278	0.4221	114	0.2105	0.4095
Deflationary	yes	−	79	0.1139	0.3197	114	0.0789	0.2708
InflationaryDecreasing	yes	0	79	0.4177	0.4963	114	0.4825	0.5019
InflationaryFixed	yes	0	79	0.1013	0.3036	114	0.1053	0.3082
InflationaryFixedInflation-Rate	yes	0	79	0.0506	0.2206	114	0.0439	0.2057
InflationaryDynamic	yes	0	79	0.1772	0.3843	114	0.1404	0.3488
Inflationary	yes	0	79	0.7468	0.4376	114	0.7719	0.4214
RewardCoinbase	yes	+	79	0.6582	0.4773	114	0.6930	0.4633
RewardInflation	yes	+	69	0.3165	0.4681	114	0.2632	0.4423
Panel D: Transactions								
TheoreticalBlockTime (seconds)	no	−	73	99.65	175.53	105	127.16	197.43
BlockTimeAverage (seconds)	no	−	76	97.83	170.27	106	127.55	196.0435
BlocksizeLimit	yes	−	60	0.7333	0.4459	91	0.7473	0.4370
TransactionFeeObligation	yes	−	77	0.7143	0.4547	111	0.6577	0.4766
NoTipSpecialTreatment	yes	+	73	0.4384	0.4996	105	0.4000	0.4922
NoFeeTipForMinerForger	yes	−	79	0.2025	0.4045	114	0.1667	0.3743
Panel E: Usability								
IntentionPayment	yes	0	79	0.3291	0.4729	114	0.4035	0.4928

Table 1 (continued)

Variable	Binary	Predicted influence	As of December 2020			All-time		
			Obs.	Mean	Std. Dev.	Obs.	Mean.	Std. Dev.
IntentionSmartContract	yes	+	79	0.3671	0.4851	114	0.3070	0.4633
IntentionOther	yes	+	79	0.3038	0.4628	114	0.2895	0.4555
SmartContractSupport	yes	0	79	0.6835	0.4681	114	0.5789	0.4959
UsageBeyondPayment	yes	+	79	0.4430	0.4999	114	0.3947	0.4910
Panel F: General								
LedgerOther	yes	0	79	0.0633	0.2450	114	0.0702	0.2566
AccountingBalance	yes	+	79	0.5316	0.5022	114	0.4561	0.5003
Anonymous	yes	+	78	0.2692	0.4464	113	0.2832	0.4526
Pseudoanonymous	yes	−	78	0.7051	0.4589	113	0.6991	0.4607
NonAnonymous	yes	+	78	0.0641	0.2465	113	0.0442	0.2066

Maintaining the different design feature groups, this table lists the variables introduced in Section 2.1 and summarizes its expected influence on market capitalization. Additionally, the columns on the right provide descriptive statistics for each variable. We consider (i) all cryptocurrencies in our sample in their design configuration as of December 2020 and (ii) all cryptocurrencies in our sample including all of their historical design feature combinations. Since we do not include the specific hash functions into our empirical analysis, we do not attempt to predict their influences on market valuation

cies in the sample at any point in time during the sample period. Upon publication of the paper we will make this dataset available via the homepage of the journal.

Despite our attempts to collect data on all design features introduced for all cryptocurrencies in our sample, there are some variables with missing observations. These include *RewardInflation* (10 missing entries), *TheoreticalBlockTime* (6 missing entries), *BlockTimeAverage* (3 missing entries), *BlocksizeLimit* (19 missing entries), *TransactionFeeObligation* (2 missing entries), *NoTipSpecialTreatment* (6 missing entries), and the degree of anonymity (1 missing entry).

2.3 Summary statistics

Table 1 shows summary statistics (number of observations, mean and standard deviation) for all design feature variables, both for the all-time data set (the one that contains soft-forked cryptocurrencies) and for our main data set containing 79 cryptocurrencies in their design configuration as of December 2020. We describe summary statistics for the latter data set. This description not only characterizes our sample but also offers an overview of the designs of the most important cryptocurrencies. We note that in some cases the categories we have created to capture alternative specifications of a design feature are not mutually exclusive. As a consequence, the fractions shown in Table 1 can add up to more than 100%.[22]

We find that approximately half of the cryptocurrencies were developed by private, for-profit entities, 27.9% by not-for-profit organizations, and 20.3% by networks of independent developers. In 64.6% of the cryptocurrency networks decisions on major code changes

[22] Consider, for example, the three dummy variables which capture the consensus mechanism (*ConsensusPoW, ConsensusPoSdPoS, and ConsensusOther*). Three cryptocurrencies use a combination of consensus mechanisms, for each of which we assign a value of one to two of the corresponding variables. Therefore, the means shown in the table add up to 1.038.

and/or decisions on governance issues are passed on to the network members. This figure implies that some networks developed by for-profit entities still involve the users in the development process. We further find that nearly all networks have publicly available core codes, and that most cryptocurrency networks are either using either C++ (∼39.2%) or Go (∼36.7%). About 50% of the cryptocurrencies were forked from another network, while the others were built from scratch.

31.7% of the cryptocurrencies in our sample use a consensus mechanism based on PoW. PoS or dPoS are more widely used (49.4%), and 22.8% of the cryptocurrencies use other consensus mechanisms. These figures are in line with the observation made by Irresberger et al. (2020), that proof of stake is becoming more popular. The most widely used hash function is Bitcoin's SHA-256 (43.0%), followed by HashEthash (15.2%). Although different elliptic curves can theoretically be used for signature generation, most coins use the two standard digital signing algorithms ECDSA (63.3%) and Ed25519 (34.2%).

Of the 79 cryptocurrencies in our sample, 27 (34.2%) have no supply cap. 22.8% of the coins have a fixed supply while 11.4% are deflationary. Of the cryptocurrencies with increasing supply (74.7%), most have adopted a scheme with decreasing growth rates (41.8% of the total, equivalent to 56% of the inflationary currencies). The alternative growth schemes are less popular. In about two thirds of the networks in our sample, the verifying agents are rewarded with coinbase rewards. An inflationary reward scheme is used by 31.7% of the networks.

The summary statistics of the design features in the category "transactions" indicate that the average theoretical blocktime amounts to 99.65 seconds with a standard deviation of 175.53. The blocktime that is actually observed in the market is slightly lower, at 97.83 seconds with a standard deviation of 170.27.[23] Of the 60 cryptocurrencies for which we could infer whether a blocksize limit exists, approximately three quarters (73.3%) have such a limit in place. 71.4% of the networks require their users to pay a mandatory transaction fee, and 56.2% allow a prioritization of transactions by paying a tip. In 20.3% of the cryptocurrency networks in our sample, transaction fees and/or tips are not included in the rewards for miners and stakers.

Turning to the variables in the "usability" group, we find that the original intention of the cryptocurrencies in our data set is roughly evenly distributed across the categories payment system, smart contract platform, and other. 68.4% of the cryptocurrency networks support smart contracts within their core code implementation, and in 44.3% of the networks coin holdings are associated with further rights, such as voting rights, or enable usages beyond pure transaction purposes.[24]

The overwhelming majority (93.7%) of the networks in our sample use a blockchain-based ledger. Only 6.3% use alternative ledgers. More than half (53.2%) of the cryptocurrencies use a balance accounting scheme, leaving 46.8% for UTXO accounting. With respect to the degree of anonymity, a strong majority (70.5%) of the networks allows pseudonymous transactions (as is also the case in the Bitcoin network). 26.9% are fully anonymous while only 6.4% of the networks require the disclosure of the real world identities of their users.

[23] If we only consider those observations where both theoretical and actual blocktimes are available, we observe an average theoretical blocktime of 99.11 seconds and an average actual blocktime of 99.43 seconds.

[24] Binance coin is an example of a coin that provides such additional usage. The coins in this network can be used to pay for several fees when using the centralized exchange Binance, such as listing fees.

3 Empirical methodology

3.1 Two-stage regressions and LASSO

We aim to empirically analyze which design features from our taxonomy have explanatory power for the cross-sectional valuation of cryptocurrencies. To identify those that significantly affect the value of cryptocurrencies, we regress two different measures of market valuation on the design feature variables introduced in Section 2. Our empirical design is characterized by a low number of observations (the 79 cryptocurrencies) and a large number of explanatory variables, making a standard regression analysis unlikely to yield reliable results. To tackle the issue of overfitting, we use two methodological approaches, a two-step regression approach inspired by Karnaukh et al. (2015) and LASSO (least absolute shrinkage and selection operator) regressions.

The two-step regression approach proceeds as follows. We first estimate six separate regressions with the respective market valuation measures as the dependent variable and the design features of one of our six categories as independent variables ("intra-group regressions"). Those variables with the highest explanatory power are then included as independent variables in the second-step regression ("encompassing regression"). We judge the explanatory power by the p-values in the intra-group regressions and use different cut-off values (0.3, 0.2 and 0.1). We further include the age of the cryptocurrencies in the encompassing regression.

The LASSO regressions integrate variable selection and regularization, thereby enhancing prediction accuracy and interpretability of the results (Lee 2020).[25] Specifically, we perform a 10-fold cross validation with random subsets selection to determine the tuning parameter λ that minimizes the mean squared error (MSE) for the LASSO regression with intercept. Based on the value of λ, the LASSO is then applied on the entire data set to determine the model's parameter estimates and the intercept. We repeat this procedure 10, 000 times in order to base our inference on a broad range of different training and validation data subset compositions.[26]

The majority of our independent variables (i.e., the design characteristics) are time-invariant. We therefore use time-series averages of the dependent variables to eliminate effects that may be specific to individual days. As noted in Section 2.2, the 79 cryptocurrencies in our sample are those with the highest market capitalization as of September 2020. To alleviate endogeneity issues, we use market valuation data averaged over all days of the fourth quarter of 2020 in our main analysis. We show results for alternative specifications in Section 4.2.

[25] Compared to a standard linear regression (with intercept), a penalty term $\lambda \sum_{j=1}^{n} \mid \beta_j \mid$ is introduced and the algorithm's objective is to minimize $\sum_{i=1}^{n} \left(y_i - \alpha - \sum_j x_{ij}\beta_j \right)^2 + \lambda \sum_{j=1}^{n} \mid \beta_j \mid$, see e.g., Tibshirani (1996). The choice of λ is crucial. The higher λ, the more variables are eliminated, but the deviation of estimated values from observed data increases. If λ is low instead, more variables are selected and the variation in the predictions decreases.

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

3.2 Variable definitions

Dependent variables: market valuation data We measure market valuation by market capitalization and a discounted version of the market capitalization. The calculation of market capitalization requires data on cryptocurrency prices and circulating supply. We obtain the former from the APIs of the respective exchange and from cryptocurrency data provider Kaiko, while the latter is obtained from Messari.[27]

The price data that we use is a daily volume-weighted average of the prices of nine cryptocurrency exchanges.[28] Whenever a cryptocurrency is traded against USD on an exchange, we refer to the resulting prices as direct prices. Not every cryptocurrency is traded against USD on every exchange. Therefore, direct prices are not always available. However, these cryptocurrencies are usually traded against BTC, and BTC is traded against USD. We use these two prices to calculate an implicit USD price of the cryptocurrency under consideration and refer to these implicit prices as indirect prices.[29] In doing so we implicitly assume that USD and BTC quotes are consistent. One exchange, Binance, is an exception. It does not trade cryptocurrencies against USD, but it does trade them against EUR. We calculate indirect prices for those cryptocurrencies traded against EUR on Binance by combining the EUR price of the currency with the EUR-USD exchange rate (obtained from exchangerate.host).[30] To check the reliability of the indirect prices we calculate indirect prices for cryptocurrency-exchange combinations for which direct prices are also available. We observe average differences below 1% for almost all combinations.

There are different ways how we could construct our final data set. We could use direct prices where available and use indirect prices only when direct prices are unavailable, or we could generally use indirect prices. We opt for a combination of these procedures. We use indirect prices when only these are available, and we use a volume-weighted average of direct and indirect prices when both are available.[31] We end up with one price for each

[27] Pricing data from Kaiko is used only in case there are missing values in the API data. Messari provides cryptocurrency data and is recommended by Kaiko as a source for circulating supply. Circulating supply excludes coins/tokens from the outstanding supply that are (i) restricted by any contracts, e.g., on-chain-lockups, or (ii) are held by projects/foundations without selling intention (see https://messari.io/report/messari-proprietary-methods).

[28] We originally obtained data of the following ten exchanges from Kaiko: Binance, Bitfinex, Kraken, Bitstamp, Coinbase, bitFlyer, Gemini, itBit, Bittrex, and Poloniex. These exchanges are considered reliable, meaning that they do not report inflated volume (see Härdle et al. (2020); on the importance of reliable data in the context of cryptocurrency trading data, see Alexander and Dakos (2020); on the prevalence of inflated trading volume among unregulated cryptocurrency exchanges, see Cong et al. (2023)). We exclude Poloniex because the only fiat currency traded on this exchange is Malaysian ringgit (RM). Due to the low liquidity between RM and USD, we refrained from converting the RM quote to a USD quote via the RM-USD rate.

[29] For example, the price of ABBC Coin (ABBC) in USD is not available on Bittrex, but Bittrex trades ABBC against BTC and BTC against USD. With $\frac{USD}{ABBC} = \frac{BTC}{ABBC} \cdot \frac{USD}{BTC}$, we obtain the Bittrex USD price of ABBC coins.

[30] We are aware of the fact that there are arbitrage opportunities resulting from price discrepancies in the cryptocurrency market (see e.g., Makarov and Schoar (2020) and Chu et al. (2024)). We note, though, that the exchanges in our sample are among the most liquid cryptocurrency exchanges, and higher liquidity is usually associated with higher market efficiency. Furthermore, the cryptocurrency market has generally become more efficient over time (Noda 2021; Köchling et al. 2019; Kristoufek and Vosvrda 2019).

[31] We do this to alleviate endogeneity concerns. Indirect prices may be systematically biased, and it is more likely that a cryptocurrency with low market capitalization is not directly traded against USD. Note that our results are qualitatively similar when we use indirect prices throughout.

cryptocurrency-exchange pair that is either an indirect price or a weighted average of direct and indirect prices. These prices are then used to calculate the weighted average price across the nine exchanges. We then multiply this weighted average price by the circulating supply to obtain our measure of market capitalization (referred to as *plain* market capitalization in the sequel).

The cryptocurrencies in our sample are of very different age. For instance, the genesis block of Bitcoin was created in January 2009 while Avalanche was just introduced in mid-September 2020. On average, cryptocurrencies that are older and more established are associated with higher market capitalization, possibly because of network effects (Metcalfe 2013; Alabi 2017) and/or because older cryptocurrencies tend to be less volatile (Kim 2015; Hafner 2020; Nabilou and Prüm 2019) and thus are better suited to act as a store of value. In addition, an older cryptocurrency may have established a "brand value" and customer loyalty. Older cryptocurrency networks may also be less impacted by adverse news.[32] These factors might result in higher market capitalization. Finally, these cryptocurrencies also benefit from the overall enhancement of the entire cryptocurrency market. Therefore, in addition to the "plain" market capitalization we also analyze discounted market valuation. Specifically, we adapt the fund size scaling procedure of Pástor et al. (2015) and calculate the discounted market capitalization of cryptocurrency *i* at time *t* according to

$$DiscountedMCap_{i,t} = MCap_{i,t} \cdot \frac{CRIX_{Genesis_i}}{CRIX_t} \tag{1}$$

with $CRIX_{Genesis_i}$ and $CRIX_t$ denoting the value of the CRIX (see e.g., Trimborn and Härdle (2018)), a widely used cryptocurrency market index, at the genesis date of coin *i* and at time *t*, respectively. For the seven cryptocurrencies in our data set that were launched prior to the CRIX, i.e. before July 31, 2014, we set $CRIX_{Genesis_i}$ to the CRIX's initial value of 1000. Intuitively, the procedure described by Eq. 1 deflates the value of cryptocurrency *i* at time *t* to its launch date.

For either methodological approach, we control for outliers by winsorizing the top three cryptocurrencies according to market capitalization (Bitcoin, Ethereum, and Ripple) and discounted market capitalization,[33] respectively. We rescale the market capitalization variables to the range $[0, 1]$ in order to obtain coefficient estimates of a convenient magnitude. As a robustness check we also estimate an alternative specification that, instead of winsorizing, uses the log of the plain and discounted market valuation as dependent variables. We obtain results (not tabulated) that are qualitatively similar to those reported in the paper.

[32] Bianchi (2020), Finck (2018), Jo et al. (2020), Koutmos (2023) and Polasik et al. (2015) argue that the cryptocurrency market heavily relies on sentiment and perceives blockchains as an immature yet evolving technology. Well-performing cryptocurrencies are associated with positive sentiment and may already have established use cases. Generally, such networks have been in existence for a longer period, making them less susceptible to negative news overall.

[33] When considering different time horizons to calculate the time-series average of the discounted market capitalization, we notice that the top three cryptocurrencies are more than five interquartile ranges above the third quartile and therefore should be considered as outliers. Note that the top three cryptocurrencies are not always the same - for example, in the fourth quarter of 2020, the top three cryptocurrencies according to discounted market capitalization are Bitcoin, Polkadot and EOS.

Independent variables: design feature data Irrespective of the methodology applied we furthermore reduce the number of independent variables by conflating some of them. Specifically, we do not include the variables *CodeGo* and *CodeOther* but rather the binary variable *CodeNonC++* which is set to 1 if at least one of the former variables is 1, and 0 otherwise. Similarly, we introduce the binary variable *CodeNonECDSA* to identify networks which do not use ECDSA for signature generation. Within the design feature group usability, we combine *IntentionSmartContract* and *IntentionOther* to the new variable *IntentionNonPayment*. Moreover, we do not include the variables that identify the different types of inflationary supply curves but restrict ourselves to the aggregated variable *Inflationary*. Finally, as already mentioned in Section 2.1, we do not include the specific hash function variables in our regression analysis but rather only include the age of the hash function.

Several of our independent variables are exhaustive sets of dummy variables (such as *CodeC++* and *CodeNonC++*). Given this, we define the base case such that the constant in our regression captures the value of a network that has a Bitcoin-like combination of design features, with all other variables equal to zero. This includes the exclusion of the dummy variables that correspond to the design of the Bitcoin network while their mutually exclusive counterparts are maintained. Additionally, we recalculate actual blocktimes and the age of the hash function according to

$$BlockTime = \frac{TheoreticalBlocktime_{Bitcoin} - BlockTimeAverage}{TheoreticalBlocktime_{Bitcoin}} = \frac{600 - BlockTimeAverage\,[s]}{600} \tag{2}$$

and

$$HashAge = \frac{HashAge_{Bitcoin} - HashAge}{HashAge_{Bitcoin}}, \tag{3}$$

respectively. This ensures the consistency of our base case definition. Note that Bitcoin has the highest theoretical blocktime (10 minutes) and employs the oldest hash function in our sample (SHA-256). Consequently, these modified variables approach zero for Bitcoin (*BlockTime*) or are equal to zero for Bitcoin (*HashAge*), while assuming positive values for other cryptocurrencies in our sample. We further rescale the two variables to the interval [0,1]. Positive values indicate a blocktime lower than the theoretical blocktime of Bitcoin (implying higher throughput of the network as compared to Bitcoin), and a hash function younger (and thus arguably more secure) than that used by the Bitcoin network, respectively.

4 Results and discussion

In this section, we present our empirical results. We present the main results, based on average market capitalization (both plain and discounted) in the fourth quarter of 2020 in Section 4.1. In Section 4.2 we then show that we obtain qualitatively similar results when we vary the period over which we measure market capitalization.

4.1 Main results

In Table 2 we show the results for the plain market capitalization. Panel A (columns 1-4) shows the results of the two-stage regression analysis while Panel B (columns 5-8) shows the LASSO results. We start with the presentation of the two-stage regression results. The four columns of Panel A show the results of the encompassing regression. The corresponding intragroup regression results that determine the set of variables to be included in the encompassing regression are shown in Appendix A. Column 1 (2, 3) shows the results that we obtain when all variables with a p-value below 0.1 (0.2, 0.3) in the intragroup regression are included in the encompassing regression. Column 4 shows the results that we obtain when all independent variables are included in the encompassing regression.[34] Note that the F-statistics shown in the last line indicate that the independent variables have significant explanatory power for the market capitalization of the cryptocurrencies only in columns 1, 2 and 3, but not in column 4 where all independent variables are included. This finding supports our choice of the two-stage regression design.

The encompassing regressions of the two-step regression approach yield three main results. First, the age of a cryptocurrency network, as measured by the variable *DaysAge* (the number of days since the launch of the genesis block, rescaled to the range $[0, 1]$), is positively related to market capitalization.[35] Second, spin-offs from other cryptocurrencies (forks) have significantly lower market values. This result is in line with our argument that such networks are almost identical copies of already existing cryptocurrencies (i.e., their respective parent networks), and that this lack of innovation negatively affects valuation. Third, we find that a configuration of design features similar to that of Bitcoin is associated with higher valuation. Remember that we defined our dummy variables such that they essentially capture deviations from the Bitcoin design, and that the continuous variables *HashAge* and *BlockTimeAverage* take on the value zero for the Bitcoin network and positive values for other cryptocurrencies in the sample. The observation that most coefficient signs in Table 2 are negative thus implies that deviations from the Bitcoin design result in lower valuation. This result may be due to the first mover advantage of the Bitcoin network and the fact that cryptocurrency users and investors are better informed about the details of Bitcoin than about those of its contenders.

We now turn to the discussion of the LASSO results. Importantly, the LASSO results are independent of the way in which we sort our independent variables into the categories of our taxonomy because the LASSO procedure considers all independent variables simultaneously and equally. In Fig. 1 we graphically illustrate for the first 200 (out of a total of 10,000) simulations the variables which were selected by the procedure and the magnitude of the coefficient estimates. The lines represent the independent variables and the columns the 200 simulation runs. Green (red) color indicates a positive (negative) coefficient estimate, and the intensity of the color represents the magnitude of the estimate. We show numerical results in columns 5 to 8 of Table 2. In column 5 we show the frequency with which a variable is selected. In columns 6 and 7 we show, conditional on a variable

[34] The number of observations is lower in columns 3 and 4 than in columns 1 and 2 because variables with missing values (such as *BlockTimeAverage*) are included in columns 3 and 4, but not in columns 1 and 2.

[35] The variable *DaysAge* potentially correlates with some other predictors. When we exclude *DaysAge* from the regression model we still observe the same significant effects, and no other variable shows up to be consistently significant.

Table 2 Market capitalization regression analysis of fourth quarter 2020

	Market capitalization							
	Panel A: Encompassing regression				Panel B: LASSO			
	(1) $p < 0.1$	(2) $p < 0.2$	(3) $p < 0.3$	(4) All	(5) Included	(6) Positive	(7) Negative	(8) ∅ coefficient
Constant	0.133	0.311*	0.367*	0.084	100%	100%	0%	0.024
	(0.112)	(0.159)	(0.216)	(0.384)				
DaysAge	0.583***	0.454**	0.486**	0.724*	80.86%	100%	0%	0.166
	(0.189)	(0.211)	(0.229)	(0.417)				
DeveloperNPO			−0.057	−0.151	0%	-	-	0
			(0.120)	(0.198)				
DeveloperPrivate	−0.066	−0.045	−0.110	−0.241	23.02%	0%	100%	−0.006
	(0.071)	(0.076)	(0.111)	(0.177)				
NoMajorityChanges				−0.021	0%	-	-	0
				(0.128)				
CodeNonC				0.235	2.75%	100%	0%	0.000
				(0.142)				
CodeNonPublic				0.002	2.75%	0%	100%	0.000
				(0.291)				
Fork	−0.132*	−0.164**	−0.193**	−0.226*	28.19%	0%	100%	−0.025
	(0.068)	(0.072)	(0.077)	(0.124)				
ConsensusPoSDPoS	−0.023	−0.138	−0.079	−0.105	2.03%	0%	100%	−0.000
	(0.083)	(0.123)	(0.139)	(0.200)				
ConsensusOther		−0.150	−0.109	0.051	0%	-	-	0
		(0.126)	(0.147)	(0.218)				
HashAge	−0.153	−0.232	−0.104	0.005	17.38%	0%	100%	−0.003
	(0.121)	(0.140)	(0.168)	(0.271)				
CurveNonECDSA				−0.013	0%	-	-	0
				(0.143)				
NoMaxSupply				0.079	0%	-	-	0
				(0.199)				

Table 2 (continued)

	Market capitalization							
	Panel A: Encompassing regression				Panel B: LASSO			
	(1) $p < 0.1$	(2) $p < 0.2$	(3) $p < 0.3$	(4) All	(5) Included	(6) Positive	(7) Negative	(8) ∅ coefficient
SupplyCirculation				0.105	0%	-	-	0
				(0.242)				
Deflationary				0.064	0%	-	-	0
				(0.182)				
FixedSupply		−0.051	−0.013	0.001	0%	-	-	0
		(0.086)	(0.095)	(0.170)				
RewardCoinbase			−0.019	0.085	0%	-	-	0
			(0.099)	(0.166)				
RewardInflation		−0.023	0.040	0.261	0%			0
		(0.084)	(0.116)	(0.213)				
BlockTimeAverage			−0.125	0.013	0.16%	0%	100%	−0.000
			(0.149)	(0.228)				
TransactionFeeObligation				−0.064	0%	-	-	0
				(0.139)				
NoTipSpecialTreatment				−0.040	0%	-	-	0
				(0.116)				
NoFeeTipForMinerForger	0.107	0.126	0.085	0.117	26.19%	100%	0%	0.012
	(0.080)	(0.090)	(0.113)	(0.171)				
IntentionNonPayment				0.284	0%	-	-	0
				(0.245)				
SmartContractSupport				−0.386**	24.24%	0%	100%	−0.014
				(0.187)				
UsageBeyondPayment				−0.061	0%	-	-	0
				(0.139)				
LedgerStyleOther			0.381	0.444	39.35%	100%	0%	0.049
			(0.270)	(0.439)				

Table 2 (continued)

	Market capitalization							
	Panel A: Encompassing regression				Panel B: LASSO			
	(1) $p < 0.1$	(2) $p < 0.2$	(3) $p < 0.3$	(4) All	(5) Included	(6) Positive	(7) Negative	(8) ∅ coefficient
AccountingBalance				0.026	0%	-	-	0
				(0.183)				
Anonymous		−0.031	−0.023	−0.048	24.24%	0%	100%	−0.005
		(0.086)	(0.094)	(0.119)				
NonAnonymous			0.373	0.561	25.50%	100%	0%	0.034
			(0.228)	(0.346)				
Observations	68	68	65	59	∅ Observations:			
R^2	0.256	0.294	0.386	0.525	59			
Adjusted R^2	0.182	0.170	0.198	0.082				
F Statistic	3.491***	2.375**	2.055**	1.185	∅ R^2:			
	(df=6;61)	(df=10;57)	(df=15;49)	(df=28;30)	0.108			

This table reports results of the cross-sectional regression of the average market capitalization in the fourth quarter of 2020 on the design feature variables and provides statistics for the variable selection process when applying LASSO with cross-validation. The encompassing models (1), (2), and (3) include the design feature variables with p-values below 0.1, 0.2 and 0.3 in the intra-group regressions, respectively. We control for multicollinearity and find that all variance inflation factors (VIF) in (1) - (3) are below 4.32. Column (4) shows the results for the case that all design feature variable are included (max. VIF of 8.65). Standard errors are given in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Column (5) reports the percentage of cases in which a variable is selected by LASSO while (6) and (7) indicate the related sign of the coefficient. Column (8) reports the average of the parameter estimates indicating the economic significance

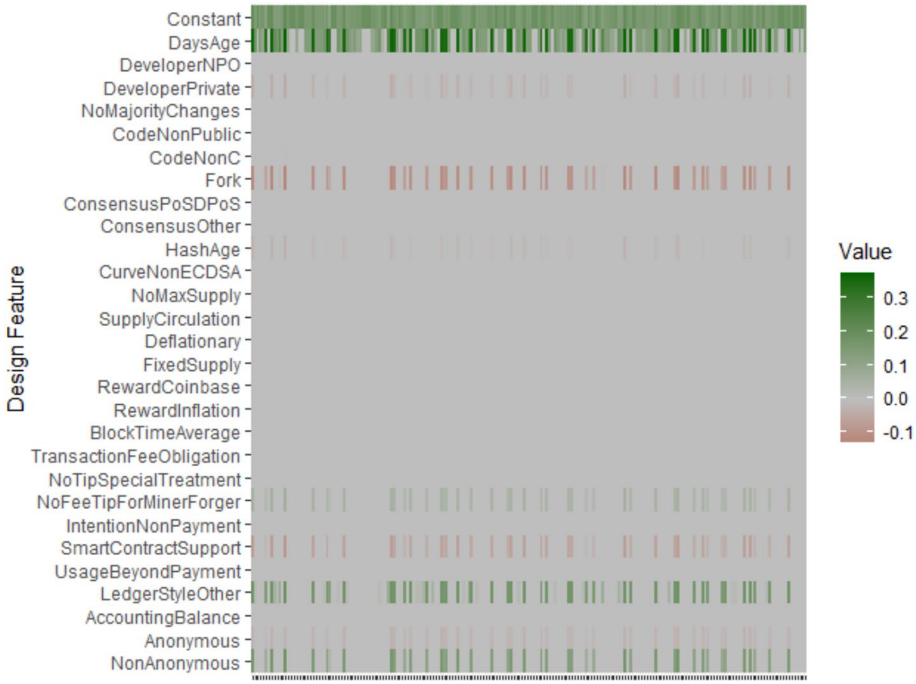

Fig. 1 LASSO variable selection and economic magnitudes (Marketcap Q4 2020). This figure shows the economic magnitude of the estimated coefficients for each design feature covering 200 randomly selected training and validation data subset compositions from our LASSO approach. Red (green) bars refer to a negative (positive) coefficient estimate, while grey bars refer to coefficient estimates equal to zero, i.e., to non-selected design features. More intense colors refer to stronger economic magnitudes

being selected, the frequency of positive and negative coefficient estimates, respectively. In column 8 we show the mean coefficient estimate.[36]

The variable that is most frequently selected (80.0% of the simulations) is the age of a cryptocurrency. Whenever selected, the coefficient estimates are, consistent with the results of the two-stage regression approach, positive. All other variables are selected much less frequently. The variable *Fork* is selected in 28.2% of the simulations and the coefficient estimates are, again in line with the regression results presented above, always negative.

The LASSO procedure further selects the variables *DeveloperPrivate* (effect sign: −), *HashAge* (−), *NoFeeTipForMinerForger* (+), *SmartContractSupport* (−), *LedgerStyleOther* (+), *Anonymous* (−), and *NonAnonymous* (+) at a reasonable frequency. In all cases the estimated direction of the effect is consistent with the sign of the coefficient estimates in the two-stage regressions.[37] The negative sign of *DeveloperPrivate* indicates that cryptocurrencies which were developed by for-profit entities have lower valuation. The negative

[36] The means are unconditional, i.e., they are calculated based on all 10,000 simulation runs. Whenever a variable is not selected, the coefficient estimate is set to 0. Conditional means (i.e., means that are calculated conditional on the respective variable being selected by the LASSO procedure) can be obtained by combining the unconditional means with the data on the selection frequency provided in column 5 of the table.

[37] Note that although the coefficient estimates were insignificant in the encompassing regression, the coefficients of the variables *DeveloperPrivate*, *HashAge*, and *NoFeeTipForMinerForger* were significant at the 10% level or better in the intra-group regressions.

impact of *HashAge* on valuation implies that, contrary to our prediction, younger hash functions, which arguably offer higher levels of security, do not increase market capitalization, ceteris paribus.[38] The positive coefficient sign of the variable *NoFeeTipForMinerForger* indicates that networks that do not pass on any transaction fees and/or tips to agents who maintain the integrity of the network have a higher market capitalization. In networks that directly reward contributions to transaction processing with fees and/or tips, transaction fees obviously play an important role. One drawback is that such transaction fees can lead to user non-participation: The fees directly cause some users to drop out, while longer waiting times cause other users who pay fees to drop out as well (Easley et al. 2019; Huberman et al. 2021; Basu et al. 2023). In addition, this can lead to adverse effects related to network security (Pagnotta 2022). Overall, these fees can increase the vulnerability of the system, which may serve to explain the positive influence of the variable *NoFeeTipForMinerForger*.

The positive coefficient signs for the variable *LedgerStyleOther* indicate that non-blockchain-based cryptocurrencies have higher market valuation. This finding should be interpreted with care, though, because our sample only contains five cryptocurrencies with that feature. The effect signs of the variables *Anonymous* and *NonAnonymous* imply that cryptocurrencies that allow completely anonymous transactions have lower market values while those that require disclosure of real-world identities have higher market values. The former result may be due to concerns that fully anonymous networks might be misused for illegal transactions.[39] The latter result may reflect the expectation of regulatory acceptance of non-anonymous cryptocurrencies.

The negative effect on market valuation ascribed to the variable *SmartContractSupport* runs counter to the intuition that a network that supports smart contracts (which enable alternative uses beyond payments) should be more valuable. However, smart contracts may also be gateways for fraudulent behavior and/or may be subject to coding errors which might result in security breaches.

We next turn to the results for the discounted market capitalization. The dependent variable is the time-series average of the discounted market capitalization (Eq. 1) during the last quarter of 2020. The analysis is otherwise identical to the one presented above. We present in Table 3 results of the two-stage regressions (columns 1-4) and the LASSO results (columns 5-8). In addition, a graphical representation of the results for the first 200 runs of the LASSO procedure can be found in Fig. 2.

The coefficient estimates for the age of the cryptocurrency (variable *DaysAge*) in the encompassing regressions are much smaller than before and are always insignificant. Furthermore, the variable is never selected by the LASSO approach. These results indicate that the discounting procedure successfully removed the effect of age on market valuation.

Regarding the influence of the design features on the market valuation, the results for discounted market capitalization are similar to those for plain market capitalization. We note, though, that the LASSO procedure selects fewer variables when we use discounted market capitalization as the dependent variable. As before, we find that spin-offs from other cryptocurrencies (variable *Fork*) have lower valuation. The respective coefficient estimate is nega-

[38] Remember that we defined the variable *HashAge* such that larger values mean younger hash functions.

[39] See the report by Europol (The European Union Agency for Law Enforcement Cooperation), available at https://tinyurl.com/4j2acsbb (accessed February 4, 2025). Auer and Claessens (2021) show that cryptocurrency prices react to regulatory news: they decrease when regulatory measures restrict the use of cryptocurrencies and they increase upon news making regulatory acceptance of cryptocurrencies more likely.

Table 3 Discounted market capitalization regression analysis of fourth quarter 2020

	Discounted market capitalization							
	Panel A: Encompassing regression				Panel B: LASSO			
	(1) $p < 0.1$	(2) $p < 0.2$	(3) $p < 0.3$	(4) All	(5) Included	(6) Positive	(7) Negative	(8) ∅ coefficent
Constant	0.168**	0.186**	0.436***	0.049	100%	100%	0%	0.189
	(0.064)	(0.068)	(0.144)	(0.371)				
DaysAge	0.101	0.100	0.016	0.175	0%	-	-	0
	(0.158)	(0.158)	(0.169)	(0.402)				
DeveloperNPO		−0.059	−0.117	−0.232	0%	-	-	0
		(0.070)	(0.103)	(0.191)				
DeveloperPrivate			−0.150	−0.303*	0%	-	-	0
			(0.093)	(0.170)				
NoMajorityChanges				0.044	0%	-	-	0
				(0.123)				
CodeNonC				0.179	0%	-	- x 0	
				(0.137)				
CodeNonPublic				−0.094	0%	-	-	0
				(0.280)				
Fork	−0.170***	−0.175***	−0.221***	−0.315**	80.52%	0%	100%	−0.066
	(0.062)	(0.063)	(0.067)	(0.120)				
ConsensusPoSDPoS				−0.002	0%	-	-	0
				(0.193)				
ConsensusOther				0.116	0%	-	-	0
				(0.210)				
HashAge				0.043	0%	-	-	0
				(0.261)				
CurveNonECDSA				0.056	0%	-	-	0
				(0.138)				
NoMaxSupply				0.091	0%	-	-	0
				(0.192)				

Table 3 (continued)

	Discounted market capitalization							
	Panel A: Encompassing regression				Panel B: LASSO			
	(1) $p < 0.1$	(2) $p < 0.2$	(3) $p < 0.3$	(4) All	(5) Included	(6) Positive	(7) Negative	(8) ∅ coefficent
SupplyCirculation				0.189	0%	-	-	0
				(0.234)				
Deflationary				0.032	0%	-	-	0
				(0.176)				
FixedSupply				−0.008	0%	-	-	0
				(0.164)				
RewardCoinbase				0.225	0%	-	-	0
				(0.160)				
RewardInflation				0.329	0%	-	-	0
				(0.205)				
BlockTimeAverage			−0.177	−0.010	0%	-	-	0
			(0.123)	(0.220)				
TransactionFeeObligation				−0.069	0%	-	-	0
				(0.134)				
NoTipSpecialTreatment				−0.091	0%	-	-	0
				(0.112)				
NoFeeTipForMinerForger	0.077	0.075	0.169**	0.199	73.74%	100%	0%	0.018
	(0.075)	(0.075)	(0.083)	(0.165)				
IntentionNonPayment				0.156	0%	-	-	0
				(0.236)				
SmartContractSupport				−0.261	0%	-	-	0
				(0.180)				
UsageBeyondPayment			0.062	0.002	0%	-	-	0
			(0.072)	(0.134)				
LedgerStyleOther				0.077	0%	-	-	0
				(0.423)				

Table 3 (continued)

	Discounted market capitalization							
	Panel A: Encompassing regression				Panel B: LASSO			
	(1) $p < 0.1$	(2) $p < 0.2$	(3) $p < 0.3$	(4) All	(5) Included	(6) Positive	(7) Negative	(8) ∅ coefficent
AccountingBalance				−0.0001	0%	-	-	0
				(0.176)				
Anonymous				−0.041	0%	-	-	0
				(0.115)				
NonAnonymous	0.400**	0.415**	0.368*	0.611*	65.97%	100%	0%	0.036
	(0.184)	(0.186)	(0.186)	(0.333)				
Observations	68	68	65	59	∅ Observations:			
R^2	0.187	0.196	0.291	0.478	59			
Adjusted R^2	0.135	0.131	0.190	−0.009				
F Statistic	3.625**	3.028**	2.878***	0.982	∅ R^2:			
	(df=4;63)	(df=5;62)	(df=8;56)	(df=28;30)	0.087			

This table reports results of the cross-sectional regression of the average discounted market capitalization in the fourth quarter of 2020 on the design feature variables and provides statistics for the variable selection process when applying LASSO with cross-validation. The encompassing models (1), (2), and (3) include the design feature variables with p-values below 0.1, 0.2, and 0.3 in the intra-group regressions, respectively. We control for multicollinearity and find that all variance inflation factors (VIF) in (1) - (3) are below 2.27. Column (4) shows the results for the case that all design feature variable are included (max. VIF of 8.65). Standard errors are given in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively. Column (5) reports the percentage of cases in which a variable is selected by LASSO while (6) and (7) indicate the related sign of the coefficient. Column (8) reports the average of the parameter estimate indicating the economic significance

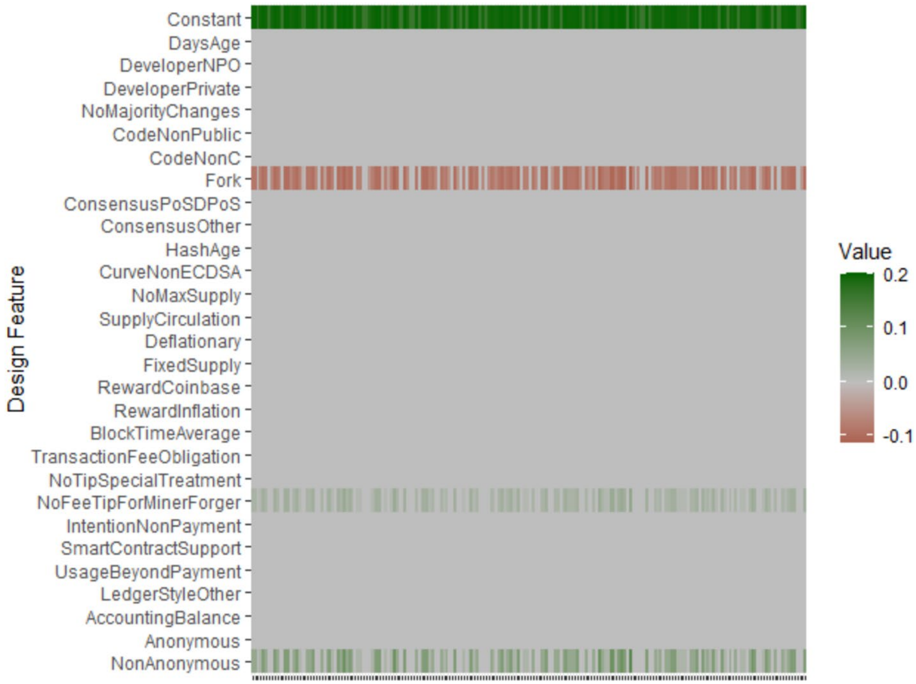

Fig. 2 LASSO variable selection and economic magnitudes (Discounted marketcap Q4 2020). This figure shows the economic magnitude of the estimated coefficients for each design feature covering 200 randomly selected training and validation data subset compositions from our LASSO approach. Red (green) bars refer to a negative (positive) coefficient estimate, while grey bars refer to coefficient estimates equal to zero, i.e., to non-selected design features. More intense colors refer to stronger economic magnitudes

tive and highly significant in the encompassing regression, and it is very frequently (80.5%) selected by the LASSO procedure, always with a negative coefficient estimate. Finally, and again consistent with our previous results, we obtain a positive coefficient estimate for the variable *NonAnonymous*. It implies that cryptocurrency networks that require disclosure of real world identities tend to have higher valuation. Furthermore, our earlier result that networks in which agents who verify transactions are rewarded by a scheme independent of fees and/or tips have a higher market valuation is also confirmed. The respective coefficient estimate (variable *NoFeeTipForMinerForger*) in the encompassing regressions is always positive (significantly so in one case), and the variable is frequently selected (73.7%) by the LASSO procedure, always with a positive coefficient sign. Finally, there is still (albeit weak and only in the two-stage regression analysis) evidence that cryptocurrencies developed by private for-profit entities are less valuable. We no longer find evidence that younger hash functions are associated with lower valuation, nor is there evidence that fully anonymous networks are less valuable.

4.2 Robustness

So far we have analyzed whether design features can explain the average (both plain and discounted) market capitalization in the fourth quarter of 2020. While averaging over values for an entire quarter should make our results insensitive to day-to-day fluctuations in cryptocurrency prices, we still have to establish that our findings are not specific to the single quarter we have considered. For this purpose we repeat our entire analysis using the average (both plain and discounted) market capitalization over (1) the entire year 2020 and (2) the first, second and third quarter of 2020. The results for the full year are shown in Tables 6, 7, 8, and 9 in Appendix B. The results for quarters 1 to 3 are qualitatively similar to those reported in the paper and are omitted.

The two-stage regression approach for the plain market capitalization averaged over the full year (Table 6) fully confirms the three main results highlighted previously. Older cryptocurrencies have higher market valuation, forks have lower market capitalization, and deviations from the Bitcoin design are associated with lower market capitalization. The latter conclusion, as before, follows from the fact that the overwhelming majority of the coefficients of the encompassing regression are negative, and that we have defined all independent variables such that their values for the Bitcoin network are zero. The results in Table 6 also confirm our previous finding that networks where the rewards of agents who verify transactions are independent of fees and/or tips have higher valuation. The LASSO results in Table 7 are fully consistent with those discussed previously. Furthermore, they are also consistent with the LASSO results in Table 2 in that the variables *DeveloperPrivate* (effect sign: −), *HashAge* (−), *SmartContractSupport* (−), *LedgerStyleOther* (+), *Anonymous* (−), and *NonAnonymous* (+) are again selected at reasonable frequencies, and have the same coefficient signs as in Table 2.

The results for the discounted market valuation, averaged over the entire year 2020 (Tables 8 and 9), again support all previous conclusions. The age of a cryptocurrency does not significantly affect its discounted market capitalization, forks have lower valuation, and most coefficient estimates in the encompassing regressions are negative, implying that deviations from the Bitcoin design are associated with lower valuation. Furthermore, the result that non-anonymous networks have higher value is confirmed, as is the previous result that networks in which transactions fees and/or tips are not passed to agents maintaining the network's integrity at all have higher market capitalization. Even the (weak) evidence that cryptocurrencies developed by private for-profit entities are less valuable is confirmed.

5 Conclusion

In this paper we analyze whether the value of cryptocurrencies as measured by their market capitalization can be related to specific cryptocurrency design features. To this end we first propose a taxonomy of cryptocurrency design features and Hand-collect a data set that contains these features for 79 cryptocurrencies. We then use two different methodological approaches, a two-stage regression analysis in the tradition of Karnaukh et al. (2015) and LASSO regressions, to analyze whether any of these design features are cross-sectionally related to cryptocurrency valuation. To account for the potential effect of the age of a cryptocurrency on its value we repeat the analysis using discounted instead of plain market capitalization as our dependent variable.

We find that cryptocurrencies spun off from other cryptocurrencies (i.e., forks) tend to have lower value. On the other hand, cryptocurrencies where agents who verify transactions are rewarded by a scheme independent of fees and/or tips tend to be more valuable. Interestingly, cryptocurrencies that require the disclosure of the real-world identities of its users have higher values, possibly in expectation of easier regulatory approval of these networks. Apart from that we find that deviations from the design of Bitcoin tend to be associated with lower valuation. Thus, even though Bitcoin may not be the most technologically advanced cryptocurrency, users and investors apparently value its design.

Overall, we provide evidence that design features partly affect the market valuation of cryptocurrencies. Due to the relatively new underlying technology of cryptocurrencies and its complexity, investors might not be aware of crucial design feature differences between the different cryptocurrency networks. Thus, they might not value the technology per se, but rather hope to invest in the “next Bitcoin”.

While we consider the impact of a large number of design features on cryptocurrency valuation, we do not take into account interactions between different design features. Such interactions may be relevant, though. For instance, the influence of shorter blocktime in a PoS network is expected to be positive due to the higher throughput enabled by shorter blocktimes. In contrast, if the blocktime is too small in a PoW network, attacks on the network by fraudulent agents may become more likely which, in turn, may result in more reluctant network adoption and eventually in reduced market capitalization. Extending our research approach to incorporate such interaction effects is a promising avenue for future research. Further, our paper offers a focused analysis of the effect of cryptocurrency design on valuation, recognizing that other variables may also affect the cross-section of cryptocurrency market values. For example, different cryptocurrencies may be held by different investor groups, and consequently may be affected by sentiment in different ways. Furthermore, the availability and liquidity of secondary markets for a cryptocurrency might affect its valuation. Future research may take these and other aspects into account and provide a more comprehensive view of cryptocurrency valuation.

A Results of the intra-group regressions in the main analysis

Table 4 Intra-group market capitalization regressions of fourth quarter 2020

	Market capitalization					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.406***	0.397***	0.323***	0.325**	0.270***	0.204***
	(0.000)	(0.000)	(0.003)	(0.011)	(0.000)	(0.001)
DeveloperNPO	−0.145					
	(0.224)					
DeveloperPrivate	−0.190*					
	(0.074)					
NoMajorityChanges	0.024					
	(0.772)					
CodeNonC	−0.025					
	(0.769)					
CodeNonPublic	−0.185					
	(0.397)					
Fork	−0.183**					
	(0.024)					
ConsensusPoSDPoS		−0.208**				
		(0.039)				
ConsensusOther		−0.150				
		(0.179)				
HashAge		−0.280*				
		(0.056)				
CurveNonECDSA		−0.022				
		(0.766)				
NoMaxSupply			−0.011			
			(0.899)			
SupplyCirculation			−0.0003			
			(0.917)			
Deflationary			0.058			
			(0.634)			
FixedSupply			−0.136			
			(0.166)			
RewardCoinbase			−0.118			
			(0.231)			
RewardInflation			−0.126			
			(0.184)			
BlockTimeAverage				−0.199		
				(0.206)		
TransactionFeeObligation				−0.015		
				(0.873)		
NoTipSpecialTreatment				0.030		
				(0.745)		
NoFeeTipForMinerForger				0.191*		

Table 4 (continued)

	Market capitalization					
	(1)	(2)	(3)	(4)	(5)	(6)
				(0.089)		
IntentionNonPayment					−0.032	
					(0.801)	
SmartContractSupport					−0.113	
					(0.341)	
UsageBeyondPayment					0.007	
					(0.931)	
LedgerStyleOther						0.161
						(0.248)
AccountingBalance						−0.037
						(0.622)
Anonymous						−0.111
						(0.179)
NonAnonymous						0.270
						(0.214)
Observations	68	68	68	59	68	68
R^2	0.109	0.089	0.077	0.078	0.047	0.073
Adjusted R^2	0.022	0.031	−0.014	0.009	0.003	0.014
F Statistic	1.248	1.533	0.845	1.138	1.060	1.245
	(df=6;61)	(df=4;63)	(df=6;61)	(df=4;54)	(df=3;64)	(df=4;63)

This table reports results of the cross-sectional intra-group regression of the average market capitalization in the fourth quarter of the year 2020 on the design feature variables. We control for multicollinearity and find that all variance inflation factors (VIF) are below 2.6. p-values are given in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively

Table 5 Intra-group discounted market capitalization regressions of fourth quarter 2020

	Discounted market capitalization					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.320***	0.202**	0.158	0.241**	0.116*	0.125**
	(0.001)	(0.033)	(0.116)	(0.038)	(0.066)	(0.026)
DeveloperNPO	−0.149					
	(0.163)					
DeveloperPrivate	−0.119					
	(0.209)					
NoMajorityChanges	0.015					
	(0.837)					
CodeNonC	0.037					
	(0.621)					
CodeNonPublic	−0.139					
	(0.476)					
Fork	−0.210***					
	(0.004)					
ConsensusPoSDPoS		0.018				
		(0.846)				
ConsensusOther		−0.066				
		(0.525)				
HashAge		−0.111				
		(0.415)				
CurveNonECDSA		−0.046				
		(0.510)				
NoMaxSupply			−0.001			
			(0.993)			
SupplyCirculation			0.0002			
			(0.927)			
Deflationary			0.007			
			(0.950)			
FixedSupply			−0.094			
			(0.306)			
RewardCoinbase			−0.014			
			(0.882)			
RewardInflation			0.054			
			(0.543)			
BlockTimeAverage				−0.150		
				(0.297)		
TransactionFeeObligation				−0.006		
				(0.948)		
NoTipSpecialTreatment				0.028		
				(0.740)		
NoFeeTipForMinerForger				0.210**		
				(0.042)		
IntentionNonPayment					0.089	
					(0.442)	
SmartContractSupport					−0.102	
					(0.349)	
UsageBeyondPayment					0.085	

Table 5 (continued)

	Discounted market capitalization					
	(1)	(2)	(3)	(4)	(5)	(6)
					(0.245)	
LedgerStyleOther						−0.096
						(0.446)
AccountingBalance						0.057
						(0.396)
Anonymous						−0.056
						(0.456)
NonAnonymous						0.349*
						(0.078)
Observations	68	68	68	59	68	68
R^2	0.144	0.041	0.032	0.091	0.041	0.089
Adjusted R^2	0.060	−0.020	−0.064	0.024	−0.004	0.031
F Statistic	1.710	0.669	0.333	1.349	0.905	1.540
	(df=6;61)	(df=4;63)	(df=6;61)	(df=4;54)	(df=3;64)	(df=4;63)

This table reports results of the cross-sectional intra-group regression of the average discounted market capitalization in the fourth quarter of the year 2020 on the design feature variables.We control for multicollinearity and find that all variance inflation factors (VIF) are below 2.6. p-values are given in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively

B Results of the robustness analysis

Table 6 Market capitalization regression analysis of year 2020

	Market capitalization									
	(1)	(2)	(3)	(4)	(5)	(6)	(7) $p < 0.1$	(8) $p < 0.2$	(9) $p < 0.3$	(10)
Constant	0.366***	0.373***	0.270**	0.321**	0.234***	0.172***	0.119	0.382**	0.497***	0.108
	(0.091)	(0.089)	(0.094)	(0.113)	(0.060)	(0.054)	(0.101)	(0.168)	(0.180)	(0.325)
DaysAge							0.516***	0.419**	0.282	0.655*
							(0.171)	(0.183)	(0.201)	(0.355)
DeveloperNPO	−0.150							−0.022	−0.029	−0.159
	(0.106)							(0.102)	(0.104)	(0.170)
DeveloperPrivate	−0.172*						−0.043	−0.080	−0.089	−0.235
	(0.094)						(0.064)	(0.097)	(0.099)	(0.152)
NoMajorityChanges	0.008									−0.037
	(0.074)									(0.108)
CodeNonC	−0.014									0.249*
	(0.076)									(0.123)
CodeNonPublic	−0.158									0.072
	(0.197)									(0.253)
Fork	−0.170**						−0.115*	−0.175**	−0.201***	−0.191*
	(0.071)						(0.061)	(0.067)	(0.068)	(0.101)
ConsensusPoSDPoS		−0.198**					−0.030	−0.103	−0.081	−0.133
		(0.088)					(0.076)	(0.125)	(0.126)	(0.173)
ConsensusOther		−0.142						−0.109	−0.134	0.009
		(0.098)						(0.128)	(0.132)	(0.187)
HashAge		−0.280**					−0.155	−0.205	−0.215	−0.041
		(0.130)					(0.110)	(0.138)	(0.147)	(0.233)
CurveNonECDSA		−0.031								−0.046
		(0.066)								(0.120)
NoMaxSupply			0.002							0.026
			(0.079)							(0.169)
SupplyCirculation			−0.0002							0.043

Table 6 (continued)

	Market capitalization									
	(1)	(2)	(3)	(4)	(5)	(6)	(7) $p < 0.1$	(8) $p < 0.2$	(9) $p < 0.3$	(10)
			(0.003)							(0.207)
Deflationary			0.047							0.034
			(0.111)							(0.158)
FixedSupply			−0.129					−0.021	−0.008	−0.033
			(0.088)					(0.083)	(0.087)	(0.148)
RewardCoinbase			−0.090							0.082
			(0.086)							(0.131)
RewardInflation			−0.103						0.008	0.233
			(0.084)						(0.081)	(0.171)
BlockTimeAverage				−0.202				−0.130	−0.113	−0.024
				(0.141)				(0.128)	(0.133)	(0.192)
TransactionFeeObligation				−0.029						−0.084
				(0.087)						(0.120)
NoTipSpecialTreatment				0.007						−0.056
				(0.081)						(0.101)
NoFeeTipForMinerForger				0.199*			0.090	0.177**	0.119	0.125
				(0.100)			(0.072)	(0.083)	(0.097)	(0.143)
IntentionNonPayment					−0.011					0.355
					(0.107)					(0.210)
SmartContractSupport					−0.121				−0.115	−0.433**
					(0.101)				(0.085)	(0.162)
UsageBeyondPayment					0.011					−0.039
					(0.070)					(0.117)
LedgerStyleOther						0.124			0.319	0.496
						(0.118)			(0.226)	(0.375)
AccountingBalance						−0.021				0.070
						(0.067)				(0.157)

Table 6 (continued)

	Market capitalization									
	(1)	(2)	(3)	(4)	(5)	(6)	(7) $p < 0.1$	(8) $p < 0.2$	(9) $p < 0.3$	(10)
Anonymous						−0.094			−0.003	−0.026
						(0.075)			(0.082)	(0.098)
NonAnonymous						0.187				0.405
						(0.198)				(0.285)
Observations	71	71	71	61	71	71	71	67	67	61
R^2	0.107	0.103	0.067	0.099	0.049	0.054	0.245	0.331	0.383	0.564
Adjusted R^2	0.023	0.048	−0.021	0.035	0.006	−0.003	0.174	0.212	0.218	0.183
F Statistic	1.279	1.887	0.763	1.542	1.146	0.948	3.452***	2.776***	2.310**	1.479
	(df=6;64)	(df=4;66)	(df=6;64)	(df=4;56)	(df=3;67)	(df=4;66)	(df=6;64)	(df=10;56)	(df=14;52)	(df=28;32)

This table reports results of the cross-sectional regression of the average market capitalization in the whole year 2020 on the design feature variables. Columns (1) - (6) shows the coefficients for the intra-group regressions. Models (7), (8), and (9) include the design feature variables with intra-group regression p-values below 0.1, 0.2, and 0.3, respectively. We control for multicollinearity and find that all variance inflation factors (VIF) in (1) - (7) are below 2.4 and below 4.43 in (8) and (9). Column (10) shows the results for the case that all design feature variable are included (max. VIF of 8.78). Standard errors are given in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively

Table 7 LASSO variable selection for market capitalization regression of year 2020

	Market capitalization			
	(1) Included	(2) Positive	(3) Negative	(4) ∅ coefficent
Constant	100%	100%	0%	0.162
DaysAge	51.16%	100%	0%	0.082
DeveloperNPO	0%	-	-	0
DeveloperPrivate	13.27%	0%	100%	−0.002
NoMajorityChanges	0%	-	-	0
CodeNonC	1.78%	100%	0%	0.000
CodeNonPublic	0%	-	-	0
Fork	16.93%	0%	100%	−0.015
ConsensusPoSDPoS	0.27%	0%	100%	−0.000
ConsensusOther	0%	-	-	0
HashAge	14.95%	0%	100%	−0.007
CurveNonECDSA	0%	-	-	0
NoMaxSupply	0%	-	-	0
SupplyCirculation	0%	-	-	0
Deflationary	0%	-	-	0
FixedSupply	1.78%	0%	100%	−0.000
RewardCoinbase	0%	-	-	0
RewardInflation	0%			0
BlockTimeAverage	10.82%	0%	100%	−0.002
TransactionFeeObligation	0.01%	0%	100%	−0.000
NoTipSpecialTreatment	0%	-	-	0
NoFeeTipForMinerForger	16.93%	100%	0%	0.009
IntentionNonPayment	0%	-	-	0
SmartContractSupport	16.03%	0%	100%	−0.010
UsageBeyondPayment	0%	-	-	0
LedgerStyleOther	19.80%	100%	0%	0.024
AccountingBalance	0.015%	100%	0%	0.000
Anonymous	14.95%	0%	100%	−0.002
NonAnonymous	14.31%	100%	0%	0.009
∅ Observations		61		
∅ Fraction of (null) deviance explained		0.062		

This table provides statistics for the variable selection process when applying LASSO with cross-validation using the average market capitalization in the whole year 2020 as the dependent variable. Column (1) reports the percentage of cases in which a variable is selected by LASSO while (2) and (3) indicate the related sign of the coefficient. Column (4) reports the average of the parameter estimate indicating the economic significance. Deviance is defined as $2\,(loglike_{sat} - loglike)$, where $loglike_{sat}$ is the log-likelihood for the saturated model. Null deviance is defined to be $2\,(loglike_{sat} - NULL)$ with $NULL$ referring to the intercept model

Table 8 Discounted market capitalization regression analysis of year 2020

	Discounted market capitalization									
	(1)	(2)	(3)	(4)	(5)	(6)	(7) $p < 0.1$	(8) $p < 0.2$	(9) $p < 0.3$	(10)
Constant	0.324***	0.218**	0.155	0.283*	0.127**	0.129**	0.203***	0.361***	0.527***	0.205
	(0.095)	(0.096)	(0.101)	(0.120)	(0.063)	(0.056)	(0.067)	(0.110)	(0.153)	(0.383)
DaysAge							0.028	−0.053	−0.078	0.050
							(0.167)	(0.173)	(0.179)	(0.419)
DeveloperNPO	−0.164							−0.170*	−0.116	−0.214
	(0.111)							(0.098)	(0.109)	(0.200)
DeveloperPrivate	−0.133							−0.149	−0.165*	−0.329*
	(0.098)							(0.091)	(0.097)	(0.180)
NoMajorityChanges	0.010									0.039
	(0.077)									(0.128)
CodeNonC	0.058									0.194
	(0.079)									(0.144)
CodeNonPublic	−0.109									−0.053
	(0.205)									(0.298)
Fork	−0.198***						−0.159**	−0.206***	−0.225***	−0.296**
	(0.074)						(0.066)	(0.070)	(0.072)	(0.119)
ConsensusPoSDPoS		0.018								−0.012
		(0.096)								(0.204)
ConsensusOther		−0.063								0.108
		(0.106)								(0.221)
HashAge		−0.111								−0.010
		(0.141)								(0.275)
CurveNonECDSA		−0.052								0.039
		(0.072)								(0.141)
NoMaxSupply			−0.004							0.061
			(0.085)							(0.199)
SupplyCirculation			0.0001							0.178

Table 8 (continued)

	Discounted market capitalization									
	(1)	(2)	(3)	(4)	(5)	(6)	(7) $p < 0.1$	(8) $p < 0.2$	(9) $p < 0.3$	(10)
			(0.003)							(0.244)
Deflationary			−0.0001							0.004
			(0.119)							(0.187)
FixedSupply			−0.089							−0.021
			(0.094)							(0.175)
RewardCoinbase			0.010							0.209
			(0.093)							(0.154)
RewardInflation			0.060							0.276
			(0.089)							(0.201)
BlockTimeAverage				−0.160					−0.219*	−0.069
				(0.150)					(0.131)	(0.226)
TransactionFeeObligation				−0.019						−0.083
				(0.092)						(0.142)
NoTipSpecialTreatment				0.014						−0.115
				(0.086)						(0.118)
NoFeeTipForMinerForger				0.201*			0.045	0.068	0.160*	0.240
				(0.106)			(0.078)	(0.079)	(0.088)	(0.168)
IntentionNonPayment					0.067					0.137
					(0.113)					(0.247)
SmartContractSupport					−0.078					−0.269
					(0.107)					(0.191)
UsageBeyondPayment					0.090				0.060	0.031
					(0.074)				(0.076)	(0.138)
LedgerStyleOther						−0.125				0.036
						(0.122)				(0.442)
AccountingBalance						0.067				0.046
						(0.069)				(0.185)

Table 8 (continued)

	Discounted market capitalization									
	(1)	(2)	(3)	(4)	(5)	(6)	(7) $p < 0.1$	(8) $p < 0.2$	(9) $p < 0.3$	(10)
Anonymous						−0.030				0.012
						(0.077)				(0.116)
NonAnonymous						0.355*	0.402**	0.423**	0.363*	0.521
						(0.204)	(0.198)	(0.196)	(0.199)	(0.336)
Observations	71	71	71	61	71	71	71	71	67	61
R^2	0.123	0.038	0.028	0.078	0.033	0.083	0.146	0.189	0.263	0.452
Adjusted R^2	0.041	−0.020	−0.063	0.012	−0.010	0.027	0.094	0.113	0.161	−0.027
F Statistic	1.493	0.651	0.306	1.188	0.764	1.485	2.810**	2.482**	2.587**	0.943
	(df=6;64)	(df=4;66)	(df=6;64)	(df=4;56)	(df=3;67)	(df=4;66)	(df=4;66)	(df=6;64)	(df=8;58)	(df=28;32)

This table reports results of the cross-sectional regression of the average market capitalization in the whole year 2020 on the design feature variables. Columns (1) - (6) shows the coefficients for the intra-group regressions. Models (7), (8), and (9) include the design feature variables with intra-group regression p-values below 0.1, 0.2, and 0.3, respectively. We control for multicollinearity and find that all variance inflation factors (VIF) in (1) - (9) are below 2.4. Column (10) shows the results for the case that all design feature variable are included (max. VIF of 8.78). Standard errors are given in parentheses. *, **, and *** indicate statistical significance at the 10%, 5% and 1% level, respectively

Table 9 LASSO variable selection for discounted market capitalization regression of year 2020

	Discounted market capitalization			
	(1) Included	(2) Positive	(3) Negative	(4) ∅ coefficent
Constant	100%	100%	0%	0.194
DaysAge	0%	-	-	0
DeveloperNPO	0%	-	-	0
DeveloperPrivate	0%	-	-	0
NoMajorityChanges	0%	-	-	0
CodeNonC	0%	-	-	0
CodeNonPublic	0%	-	-	0
Fork	65.01%	0%	100%	−0.035
ConsensusPoSDPoS	0%	-	-	0
ConsensusOther	0%	-	-	0
HashAge	0%	-	-	0
CurveNonECDSA	0%	-	-	0
NoMaxSupply	0%	-	-	0
SupplyCirculation	0%	-	-	0
Deflationary	0%	-	-	0
FixedSupply	0%	-	-	0
RewardCoinbase	0%	-	-	0
RewardInflation	0%			0
BlockTimeAverage	0%	-	-	0
TransactionFeeObligation	0%	-	-	0
NoTipSpecialTreatment	0%	-	-	0
NoFeeTipForMinerForger	14.55%	100%	0%	0.001
IntentionNonPayment	0%	-	-	0
SmartContractSupport	0%	-	-	0
UsageBeyondPayment	0%	-	-	0
LedgerStyleOther	0%	-	-	0
AccountingBalance	0%	-	-	0
Anonymous	0%	-	-	0
NonAnonymous	30.03%	100%	0%	0.007
∅ Observations		61		
∅ Fraction of (null) deviance explained		0.035		

This table provides statistics for the variable selection process when applying LASSO with cross-validation using the average discounted market capitalization in the whole year 2020 as the dependent variable. Column (1) reports the percentage of cases in which a variable is selected by LASSO while (2) and (3) indicate the related sign of the coefficient. Column (4) reports the average of the parameter estimate indicating the economic significance. Deviance is defined as $2\,(loglike_{sat} - loglike)$, where $loglike_{sat}$ is the log-likelihood for the saturated model. Null deviance is defined to be $2\,(loglike_{sat} - NULL)$ with $NULL$ referring to the intercept model

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References

Abadi J, Brunnermeier M (2018) Blockchain economics. NBER Working Paper No. 25407

Alabi K (2017) Digital blockchain networks appear to be following Metcalfe's law. Electron Commer Res Appl 24:23–29

Alexander C, Dakos M (2020) A critical investigation of cryptocurrency data and analysis. Quant Finance 20(2):173–188

Aoyagi J, Adachi D (2018) Fundamental values of cryptocurrencies and blockchain technology. Working Paper

Auer R, Claessens S (2021) Cryptocurrency market reactions to regulatory news. In: The Routledge Handbook of FinTech. Routledge, pp 455–468

Basu S, Easley D, O'Hara M, Sirer E (2023) Stablefees: a predictable fee market for cryptocurrencies. Manage Sci 69(11):6508–6524

Bhambhwani SM, Delikouras S, Korniotis GM (2023) Blockchain characteristics and cryptocurrency returns. J Int Finan Markets Inst Money 86(12):101788

Biais B, Bisiere C, Bouvard M, Casamatta C, Menkveld AJ (2023) Equilibrium bitcoin pricing. J Financ 78(2):967–1014

Bianchi D (2020) Cryptocurrencies as an asset class? An empirical assessment. J Altern Invest 23(2):162–179

Bianchi D, Babiak M, Dickerson A (2022) Trading volume and liquidity provision in cryptocurrency markets. J Bank Finance 142:106547

Bianchi D, Babiak M (2021) Mispricing and risk compensation in cryptocurrency returns. Working Paper

Bolt W, van Oordt MR (2020) On the value of virtual currencies. J Money Credit Bank 52(4):835–862

Borri N, Massacci D, Rubin M, Ruzzi D (2022) Crypto risk premia. Working Paper

Cai CX, Zhao R (2024) Salience theory and cryptocurrency returns. J Bank Finance 159:107052

Chu G, Li X, Shen D, Urquhart A (2024) Price divergence in bitcoin market. Rev Quant Financ Account 1–42

Cong LW, Karolyi GA, Tang K, Zhao W (2022) Value premium, network adoption, and factor pricing of crypto assets. Working Paper

Cong LW, Li X, Tang K, Yang Y (2023) Crypto wash trading. Manage Sci 69(11):6427–6454

Corbet S, Larkin C, Lucey B (2020) The contagion effects of the COVID-19 pandemic: evidence from gold and cryptocurrencies. Financ Res Lett 35:101554

Cousins K, Subramanian H, Esmaeilzadeh P (2019) A value-sensitive design perspective of cryptocurrencies: a research agenda. Commun Assoc Inf Syst 45(27):511–547

Dwyer GP (2015) The economics of bitcoin and similar private digital currencies. J Financ Stab 17:81–91

Easley D, O'Hara M, Basu S (2019) From mining to markets: the evolution of bitcoin transaction fees. J Financ Econ 134(1):91–109

Fama EF, MacBeth JD (1973) Risk, return, and equilibrium: empirical tests. J Polit Econ 81(3):607–636

Fieberg C, Liedtke G, Zaremba A (2024) Cryptocurrency anomalies and economic constraints. Int Rev Financ Anal 94:103218

Fieberg C, Liedtke G, Poddig T, Walker T, Zaremba A (2024) A trend factor for the cross-section of cryptocurrency returns. J Financ Quant Anal. Forthcoming
Finck M (2018) Blockchains: regulating the unknown. German Law J 19(4):665–692
Garriga M, Dalla Palma S, Arias M, Renzis A, Pareschi R, Tamburri DA (2020) Blockchain and cryptocurrencies: a classification and comparison of architecture drivers. Concurr Comput Pract Exp 33(8):e5992
Hafner CM (2020) Testing for bubbles in cryptocurrencies with time-varying volatility. J Financ Economet 18(2):233–249
Han W, Newton D, Platanakis E, Wu H, Xiao L (2024) The diversification benefits of cryptocurrency factor portfolios: are they there? Rev Quant Financ Acc 63(2):469–518
Härdle WK, Harvey CR, Reule RCG (2020) Understanding cryptocurrencies. J Financ Economet 18(2):181–208
Hayes AS (2017) Cryptocurrency value formation: an empirical study leading to a cost of production model for valuing bitcoin. Telematics Inform 34(7):1308–1321
Hu AS, Parlour CA, Rajan U (2019) Cryptocurrencies: stylized facts on a new investible instrument. Financ Manage 48(4):1049–1068
Huberman G, Leshno JD, Moallemi CC (2021) Monopoly without a monopolist: an economic analysis of the bitcoin payment system. Rev Econ Stud 88(6):3011–3040
Irresberger F, John K, Mueller P, Saleh F (2020) The public blockchain ecosystem: an empirical analysis. NYU Stern School of Business Working Paper
Jo H, Park H, Shefrin H (2020) Bitcoin and sentiment. J Futur Mark 40(12):1861–1879
Jung W, Park H (2024) Common factors in the returns on cryptocurrencies. Financ Res Lett 65:105485
Karnaukh N, Ranaldo A, Söderlind P (2015) Understanding FX liquidity. Rev Financ Stud 28(11):3073–3108
Kim T (2015) The predecessors of bitcoin and their implications for the prospect of virtual currencies. PLoS ONE 10(4):e0123071
Köchling G, Müller J, Posch PN (2019) Does the introduction of futures improve the efficiency of bitcoin? Financ Res Lett 30:367–370
Koenraadt J, Leung E (2024) Investor reactions to crypto token regulation. Eur Account Rev 33(2):367–397
Koutmos D (2023) Investor sentiment and bitcoin prices. Rev Quant Financ Acc 60(1):1–29
Koutmos D, Payne JE (2021) Intertemporal asset pricing with bitcoin. Rev Quant Financ Acc 56:619–645
Kristoufek L, Vosvrda M (2019) Cryptocurrencies market efficiency ranking: not so straightforward. Physica A 531:120853
Lee CF (2020) Financial econometrics, mathematics, statistics, and financial technology: an overall view. Rev Quant Financ Acc 54(4):1529–1578
Leong M, Kwok S (2023) The pricing of jump and diffusive risks in the cross-section of cryptocurrency returns. J Empir Financ 74:101420
Li L, Miu P (2023) Are cryptocurrencies a safe haven for stock investors? A regime-switching approach. J Empir Financ 70:367–385
Liu Y, Tsyvinski A (2021) Risks and returns of cryptocurrency. Rev Financ Stud 34(6):2689–2727
Liu W, Liang X, Cui G (2020) Common risk factors in the returns on cryptocurrencies. Econ Model 86:299–305
Liu Y, Tsyvinski A, Wu X (2022) Common risk factors in cryptocurrency. J Financ 77(2):1133–1177
Makarov I, Schoar A (2020) Trading and arbitrage in cryptocurrency markets. J Financ Econ 135(2):293–319
Metcalfe B (2013) Metcalfe's law after 40 years of ethernet. Computer 46(12):26–31
Mislavsky R (2024) Behavioral tokenomics: consumer perceptions of cryptocurrency token design. Johns Hopkins Carey Business School Research Paper No. 25-18
Mora C, Rollins RL, Taladay K, Kantar MB, Chock MK, Shimada M, Franklin EC (2018) Bitcoin emissions alone could push global warming above 2°C. Nat Clim Chang 8(11):931–933
Nabilou H, Prüm A (2019) Ignorance, debt and cryptocurrencies: The old and the new in the law and economics of concurrent currencies. Journal of Financial Regulation 5(1):29–63
Nakamoto S (2008) Bitcoin: a peer-to-peer electronic cash system. Online, available from https://bitcoin.org/bitcoin.pdf
Noda A (2021) On the evolution of cryptocurrency market efficiency. Appl Econ Lett 28(6):433–439
Pagnotta ES, Buraschi A (2018) An equilibrium valuation of bitcoin and decentralized network assets. Working Paper
Pagnotta ES (2022) Decentralizing money: bitcoin prices and blockchain security. Rev Financ Stud 35(2):866–907
Pástor Ľ, Stambaugh RF, Taylor LA (2015) Scale and skill in active management. J Financ Econ 116(1):23–45
Pfautsch F, Schubert N, Orglmeister C, Gebhart M, Habermann P, Juurlink B (2020) The evolution of secure hash algorithms. PARS-Mitteilungen 35(1):5–15
Polasik M, Piotrowska AI, Wisniewski TP, Kotkowski R, Lightfoot G (2015) Price fluctuations and the use of bitcoin: an empirical inquiry. Int J Electron Commer 20(1):9–49

Schilling L, Uhlig H (2019) Some simple bitcoin economics. J Monet Econ 106:16–26
Shams A (2020) The structure of cryptocurrency returns. Fisher College of Business Working Paper No. 2020-03-011
Sockin M, Xiong W (2023) A model of cryptocurrencies. Manage Sci 69(11):6684–6707
Tibshirani R (1996) Regression shrinkage and selection via the lasso. J Roy Stat Soc Ser B (Methodol) 58(1):267–288
Trimborn S, Härdle WK (2018) CRIX - An index for cryptocurrencies. J Empir Financ 49:107–122
Wang S, Vergne J-P (2017) Buzz factor or innovation potential: what explains cryptocurrencies' returns? PLoS ONE 12(1):e0169556
Zhang W, Li Y, Xiong X, Wang P (2021) Downside risk and the cross-section of cryptocurrency returns. J Bank Financ 133:106246
Zimmerman P (2020) Blockchain structure and cryptocurrency prices. Bank of England Working Paper No. 855