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The marginal cost of mining, Metcalfe's law and cryptocurrency value formation: Causal inferences from the instrumental variable approach

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Abstract

This paper is the first to rigorously test commonly cited simplistic theories of cryptocurrency pricing, namely, cost-based model and Metcalfe's law, using causal inferences from the instrumental variables approach on block-level data for six proof-of-work coins. Positive effects of hashrate and transaction count implied by cost-based pricing and Metcalfe's law, respectively, are non-existent for any of the coins investigated. Negative and insignificant estimators cannot be explained by weak instruments, suggesting previously reported strong positive relationships are spurious due to autocorrelation and endogeneity. The study reinforces the need for a more sophisticated cryptocurrency valuation framework.

Keywords: cryptocurrency; blockchain; hashrate; Metcalfe's law; cost-based pricing; causal inference; instrumental variable

JEL codes: C22, C26, E42, G12

Introduction

What factors drive cryptocurrency prices? Cryptocurrency investors, blockchain enthusiasts and finance researchers alike have been pondering over this question for years. At least since 2014, various models have been developed to explain volatile and unpredictable prices of coins and tokens, from simplistic single-factor models, citing costs of mining (Hayes, 2017, 2019), adoption as number of users or as total number of transactions count (Alabi, 2017; Peterson, 2018; Van Vliet, 2018; Pele and Pele, 2019), or willingness to hold (Wang, 2014) as primary price drivers, to more complicated equilibrium-based frameworks (Pagnotta and Buraschi, 2018; Shanaev et al., 2019b).

However, the research on fundamental, theory-based cryptocurrency valuation has been rather scarce, especially compared to exclusively data-driven empirical finance research on cryptocurrencies (see, for example, Bouri et al., 2017; Ciaian et al., 2018; Corbet et al., 2018; Liu and Tsyvinski, 2018; Liu et al., 2019; Gozcek and Skliarov, in press). Simultaneously, the empirical evidence in support of two main simplistic fundamental valuation paradigms – cost-based and adoption-based pricing – is questionable and at a closer look might be spurious or inconsistent. Therefore, this study explores the relationship between factors of proof-of-work cryptocurrency value formation that are widely considered important for these two models, namely, network hashrate and transaction count, for six individual coins. It is one of the first to use causal inferences from instrumental variables in empirical cryptocurrency research. The study is able to show that both of the simplistic models do not fit the data and are consistently not accepted for all six sample coins. It, therefore, argues for the development of "second-generation valuation metrics" (Lehner et al., 2018) for cryptocurrencies, them being not uncritical extensions of modern empirical finance asset-pricing techniques but rather asset class-specific equilibrium-based and theory-driven valuation models (Pagnotta and Buraschi, 2018; Shanaev et al., 2019b).

Literature Review

Cryptocurrencies and financial economics: asset-pricing without valuation

Since the increased recognition of cryptocurrencies as an alternative investment in the 2010s, a wide spectrum of literature has been developed to apply techniques from traditional empirical finance to explore the risk-return properties of cryptocurrencies through the lens of conventional asset-pricing. However, performance attribution analysis has evidenced that cryptocurrency returns are not affected by any of the established asset markets (Bouri et al., 2017; Ciaian et al., 2018; Ciaian and Rajcaniova, 2018; Corbet et al., 2017; Corbet et al., 2018; Feng et al., 2018) or risk factors (Liu and Tsyvinski, 2018), albeit some cryptocurrency market-specific factors such as momentum, investor attention (Liu and Tsyvinski, 2018), coin market capitalisation, age and consensus mechanism (Shanaev et al., 2019a) have been shown to explain the cross-section of coin returns. Nevertheless, the Even studies that do discover interrelations between cryptocurrency markets and traditional assets specify that their findings are inconsistent (Goczek and Skliarov, in press) or conditional on cryptocurrency type (Corbet et al., 2017; Ciaian and Rajcaniova, 2018).

Recently, there has been a tentative consensus forming in the field that there is a need for "second generation valuation metrics" for cryptocurrencies (Lehman et al., 2018). Most scholars envision such a "second generation" in application of more sophisticated empirical finance techniques (such as FECM or ARJI, see, for example, Goczek and Skliarov, in press; Wang et al., in press) or in the development of multi-factor models for cryptocurrencies (Liu et al., 2019). Nevertheless, it is logically incoherent to extend these asset-pricing models originally suggested for stocks to cryptocurrencies without developing the rigorous asset class-specific valuation framework first. This argument is even accepted by the developers of market-size-momentum three-factor model for cryptocurrencies, who concede that stock-specific risk factors are based on traditional finance theories that are not directly applicable to cryptocurrencies (Liu et al., 2019). For stock markets, Fama-French (2015) multifactor models have been a logical extension of the original CAPM (Sharpe, 1964), while CAPM, in its turn, has been built on earlier share valuation models such as the dividend discount model (Miller and Modigliani, 1961; Gordon, 1963). Therefore, before the academic consensus is formed with regards to proper fundamental cryptocurrency valuation models, empirical applications of asset-pricing techniques, albeit useful for exploring general risk-return characteristics, would not yield substantial explanatory or predictive power or generate insights about sources of cryptocurrency value formation.

Existing frameworks for proof-of-work cryptocurrency valuation

The literature on fundamental valuation of cryptocurrencies is much more scarce than empirical asset-pricing studies (Bouoiyour and Selmi, 2017; Corbet et al., 2019). Apart from some recently developed equilibrium-based valuation frameworks (Pagnotta and Buraschi, 2018; Shanaev et al., 2019b), most of the simplistic single-variable models of cryptocurrency pricing can be classified as either *adoption-based* or *cost-based.*

Adoption-based models claim that cryptocurrency prices are predominantly driven by demand-side factors. They are usually derived from the application of Metcalfe's law, which states that network's value should be proportional to the squared number of users (wallets), or, equivalently, to the number of transactions. Prominent adoption-based models include Alabi (2017), Peterson (2018), Van Vliet (2019), and Pele and Pele (2019). Notably, all of the empirical studies justifying the applicability of Metcalfe's law suffer from similar econometric shortcomings: first, they regress coin price on the number of users or transactions (usually also applying a simple logarithmic transformation to both series). These models typically yield unnaturally high values of R-squared (above 0.99) and do not report any autocorrelation test results. Effectively, they can be represented as $P_t = \beta_0 + \beta_1 F_t + \varepsilon_t$ or $\ln(P_t) = \beta_0 + \beta_1 \ln(F_t) + \varepsilon_t$, where P_t is coin price at time period t and F_t is a particular fundamental variable at time period t. In financial econometrics, it is widely known that level data such as prices is serially correlated, and a log-difference transformation should be applied to it instead of a simple logarithmic transformation. In the graphical representation of the models' fit both in Van Vliet (2018) and Pele and Pele (2019), the regularities of observed prices' deviations from the expected price suggest severe autocorrelation issues, therefore the reported regressions results are probably spurious and inconsistent. In terms of more technically sophisticated studies, Goczek and Skliarov (in press) apply factor augmented error correction models to find that the only consistent positive driver of Bitcoin prices is investor attractiveness, results for Bitcoin supply, traditional asset market exposures and number of transactions being inconsistent. However, Goczek and Skliarov (in press) still use natural logarithm of Bitcoin price in their regression models instead of log-difference, possibly leading to the shortcomings outlined above. Hence, the cryptocurrency valuation field can benefit from the methodology developed in the conventional empirical finance literature, estimating the sensitivity of returns to the change in fundamental variables.

As for the cost-based modes, they have been primarily developed in the works of Hayes (2017, 2019). Hayes (2017, 2019) claimed that cryptocurrency price is mostly driven by marginal costs of mining, i.e. supply-side factors or "the cost of production". Hayes (2019) developed a valuation model and, utilising Granger causality, showed that logarithm of predicted price based on the marginal cost of mining Granger-causes market price, while market price does not Granger-cause model price. However, there are two major shortcomings in Hayes' (2019) result. First, the null hypothesis that market price does not Granger-cause cost of mining has been accepted with a p-value of 0.101 (therefore, the result was only marginally insignificant, not allowing to infer that the relationship is one-directional with sufficiently high confidence). Second, and most importantly, Granger causality has been applied to log-transformed price data (not return or log-return data), which is well-known to have unit roots. As Granger causality analysis is only applicable to stationary series (Granger, 1988), the empirical results of Hayes' (2019) study might be spurious.

Interestingly, the reliance on the cost-based framework of cryptocurrency pricing led some researchers to believe that Bitcoin constitutes ideal money for a socialist economic system as it adheres to the labour theory of value, each unit of cryptocurrency representing spent kilowatt-hours, and thus, labour (Huckle and White, 2016). Nevertheless, the notion that Bitcoin price is "backed by electricity" is common not only within such ideologically inclined circles but also among less radical authors and analysts (Granot, 2018).

Overall, it is shown that existing empirical studies on simplistic valuation frameworks suffer from spurious regressions and inadequate model design. Nevertheless, there exists another important issue associated with estimating a causal relationship between fundamental blockchain characteristics and coin price – namely, endogeneity – which is discussed in detail in the next subsection.

The uniqueness of cryptocurrencies as an asset class and the endogeneity issue

One of the main barriers to expanding fundamental analysis practices from stocks to cryptocurrencies is the absence of conventional disclosure that can be used, for example, to compute valuation multiples. Nevertheless, technically, cryptocurrency-specific disclosure is necessarily publically available and is updated at an extremely high frequency, as all essential information regarding the state of the network is stored in the blockchain. For example, the data on when the latest block was mined, how many transactions it included and how much fees miners charged becomes public knowledge almost instantly. It simultaneously presents an opportunity and poses a challenge for fundamental analysis. Unlike for stocks, where new fundamental information is released to the public in discrete "chunks", with earnings announcements and regular corporate disclosure, for cryptocurrencies each block constitutes a unique piece of disclosure of its own, leading to traditional estimation techniques such as event studies being effectively inapplicable. Moreover, in equity valuation, it can be safely assumed that stock price does not influence fundamentals, at least in the short run, and therefore the relationship between changing company characteristics and abnormal stock returns can be considered causal and unidirectional. For cryptocurrencies, this does not necessarily hold true. For example, imagine that on a particular day both network hashrate and coin price increase substantially. One could argue that it is due to cost-based valuation model: as higher hashrate, holding electricity price and ASIC efficiency constant, implies higher marginal costs of production, coin price reflected the increase in cost (Hayes, 2017, 2019). Alternatively, a price jump might have changed the incentives of miners, making mining more profitable and therefore increasing mining activity on the chain (Kroll et al., 2013). This is a clear case of an endogeneity problem – as the causal relationship between variables (here, hashrate and coin price) is not unidirectional, the regressor will be correlated with the error term, resulting in an inconsistent estimator (Angrist and Krueger, 2001).

A similar endogeneity issue can be present in case of adoption-based model: a coin price increase might be a response to the growing number of transactions and higher adoption, consistent with Metcalfe's law (Van Vliet, 2018; Pele and Pele, 2019), or be a proximate cause of the aforementioned growth in the number of transactions, as, for example, a favourable news event might increase private coin valuations and therefore lead to higher market prices and higher transaction demand. Note that such an issue is completely absent from fundamental analysis of stocks, as it is generally accepted that stock price does not influence company fundamentals in the short term, therefore the model $\ln\left(\frac{P_t}{P_{t-1}}\right) = \beta_0 + \beta_1 \ln\left(\frac{F_t}{F_{t-1}}\right) + \varepsilon_t$ will theoretically return an unbiased β_1 estimator as the regressor can be considered exogenous.

The endogeneity problem, though absent from most of the empirical research on cryptocurrency valuation, is notably briefly discussed in Polasik et al. (2015), Ciaian et al. (2016) and Bouoiyour and Selmi (2017), but even there it does not lead to significant methodological developments, therefore constituting another gap in the literature.

Granger causality and instrumental variable estimators in cryptocurrency research

Separating the two causality scenarios in an econometric estimation has been subject to rigorous theoretical and empirical research in the field. Two main econometric techniques developed to generate causal inferences are Granger causality (Granger, 1988) and instrumental variable estimators (Angrist and Krueger, 2001). The application of both in cryptocurrency finance research is associated with some notable technical and conceptual challenges.

As for Granger causality, there are several studies applying this concept to cryptocurrency fundamental analysis. Hayes (2019) provides evidence of marginal mining costs being a unidirectional Granger-cause of market prices, however, as discussed above, his analysis might not be reliable. Contrastingly, Wiedmer (2018) finds that while cryptocurrency market capitalisation Granger-causes number of open issues in the blockchain project's source code, the reverse is not true. As Wiedmer's (2018) study has reported all required tests for the applicability of the Granger causality approach, the results can be considered reliable in the econometric sense. However, when using Granger causality in finance research, particularly regarding asset price data, it is crucial to understand that efficient market hypothesis does not allow to accept the hypothesis that fundamental variables do not influence coin price if lagged fundamental variables are not jointly significant, namely because it states that all prior information is already reflected in the price. Assume, for example, that network hashrate influences Bitcoin price. Then, rational agents would estimate the expected value of future hashrate based on the past realisation of the variable, forming their private valuations accordingly. Therefore, historical data on hashrate will be already translated into current market prices and not market returns via the rational expectations channel. Therefore, one potentially apply Granger causality only to high-frequency data (i.e. individual block data) to exploit lags and slight inefficiencies in coin price responses. However, such an approach poses an issue of its own: as transaction count and especially hashrate are extremely volatile short-term, the estimators obtained using such a procedure would have extremely low statistical power, leading to a rejection of the null being effectively improbable and the approach being useless for verifying or falsifying the simplistic fundamental cryptocurrency valuation models.

A seemingly more promising method of generating causal inferences about the relationship between transaction count, hashrate and coin price is the instrumental variable approach, or two-stage least squares (TSLS) (Angrist and Krueger, 2001). It is a well-known estimation technique that is regularly applied when it is suspected regressors might be endogenous. An ideal instrument would be a variable that is not theoretically related (exogenous) to the dependent variable and has a sufficiently strong correlation with the endogenous dependent variable (has a strong first stage). Applications of IV and TSLS estimators in cryptocurrency economics and finance are virtually non-existent. Ciaian et al. (2016) come close to the concept of exogenous curve-shifters for supply and demand in case of Bitcoin, however they do not coherently apply the classical system of simultaneous equations framework with instrumental variables (Angrist and Krueger, 2001). Furthermore, the very design of proof-of-work cryptocurrencies significantly complicates system of simultaneous equation estimations as Bitcoin supply, for example, is deliberately engineered to be as inelastic as possible, therefore a sufficiently good "curve-shifter" for supply might be simply not feasible to construct. Furthermore, some researchers are sceptical about the applicability of conventional supply-and-demand reasoning to cryptocurrencies in general (Goczek and Skliarov, in press).

Bouoiyour and Selmi (2017) acknowledge the conceptual difficulty of finding proper instrumental variables for cryptocurrency price-related estimations and resort to the well-known GMM logic of using lagged dependent variables as instruments. That is controversial for finance research as past returns (lagged dependent variables) are generally uncorrelated with current returns and therefore constitute rather weak instruments. The same approach is chosen earlier by Polasik et al. (2015), who utilise lagged dependent variables as instruments, additionally proposing an original instrument candidate – the logarithmic rate of growth of cryptography-related materials in Lexis database. Such an instrument is problematic as it might not be theoretically exogenous. First, Bitcoin users or open-source code developers might contribute to the general knowledge on cryptography more intensively as specific blockchain projects develop: a similar relationship has been detected by Wiedmer (2018), reporting growing activity for Bitcoin open source code on GitHub after cryptocurrency market capitalisation increases. Second, general interest in cryptography might be an effect, not a cause, of investor or public sentiment regarding cryptocurrencies. Hence, theoretically there is little reason to assert such an instrument is sufficiently strong or exogenous.

Therefore, since neither Polasik et al. (2015) nor Bouoiyour and Selmi (2017) report any endogeneity or weak instrument tests, one can suspect lagged dependent variables or some sporadically suggested candidate instruments (such as log-difference of the number of cryptography-related entries in Lexis) are not sufficiently strong instrumental variables for the empirical testing of cryptocurrency valuation models.

Weak instruments pose a significant challenge for hypothesis testing, as in this case, insignificant estimator might mean either that the null hypothesis cannot be rejected or that the standard error is too high, reducing the statistical power of the estimation (Young, 2017).

Therefore, weak instruments tests, such as Cragg-Donald F-test (Cragg and Donald, 1993) are, although imperfect (Young, 2017), but still crucial tools for identifying true negatives in IV estimations.

Furthermore, instrumental variable methods are criticised for improper use in cases when there is little to no evidence that standard OLS estimators are biased (Young, 2017). For these reasons, Young (2017) advocates for reporting both OLS and TSLS regression results and explicitly testing for endogeneity, i.e. the significant difference between OLS and TSLS estimators.

Therefore, this study, having identified the gap in the literature with regards to causal inferences in fundamental cryptocurrency valuation models, aims at filling it while recognising the limitations of instrumental variable estimators.

Data and Methodology

Data collection

Unlike previous research that has explored fundamental valuation models solely in application to Bitcoin (Hayes, 2017; 2019; Van Vliet, 2018; Pele and Pele, 2019), this study considers six proof-of-work coins: Bitcoin, Litecoin, Bitcoin Cash, Bitcoin SV, Dash and Dogecoin. The sample characteristics for retrieved data can be consulted in Table 1.

Table 1. Sample characteristics

Coin	Sample start date	Sample end date	Number of sample days	Number of sample blocks
Bitcoin	10/01/2014	14/05/2019	1687	252,808
Litecoin	10/01/2014	14/05/2019	1687	981,676
Bitcoin Cash	02/08/2017	14/05/2019	651	104,015
Bitcoin SV	15/11/2018	14/05/2019	181	27,131
Dash	02/05/2017	14/05/2019	743	407,521
Dogecoin	02/05/2017	14/05/2019	743	1,027,525

For all six cryptocurrencies, block-level data on date and time mined, transaction count, fees in native blockchain coins, fees in USD, block size in kB and mining difficulty has been retrieved. Then, data has been aggregated daily, computing number of blocks mined, average empirical block time, the total number of transactions, total fees in native blockchain coins and USD, total block size and average difficulty. Daily coin price in USD has been calculated using transaction-weighted fees. Transaction fee density has been assessed as $\rho = \frac{Total\ fees\ in\ native\ coin}{Total\ block\ size\ in\ kB}$, and fiat transaction fee as $t_c = \frac{Total\ fees\ in\ USD}{Total\ number\ of\ transactions}$. Finally, daily hashrate has been estimated using difficulty and empirical block time: $Hashrate = \frac{2^{32} Difficulty}{Block\ time}$. As the data is aggregated daily, blockchains with varying protocol block times (~10 minutes for Bitcoin, Bitcoin Cash and Bitcoin SV, ~2.5 minutes for Litecoin and Dash and ~1 minute for Dogecoin) can be studied in the same sample. Moreover, since the impact of fundamentals on coin price price is assessed on logarithmic return level, the same models are applicable and interpretable in the case of all six cryptocurrencies.

The dynamics of coin price, hashrate and transaction count in for all six blockchains can be consulted in Figures 1a-c.

Figure 1a. The dynamics of coin prices for six blockchains

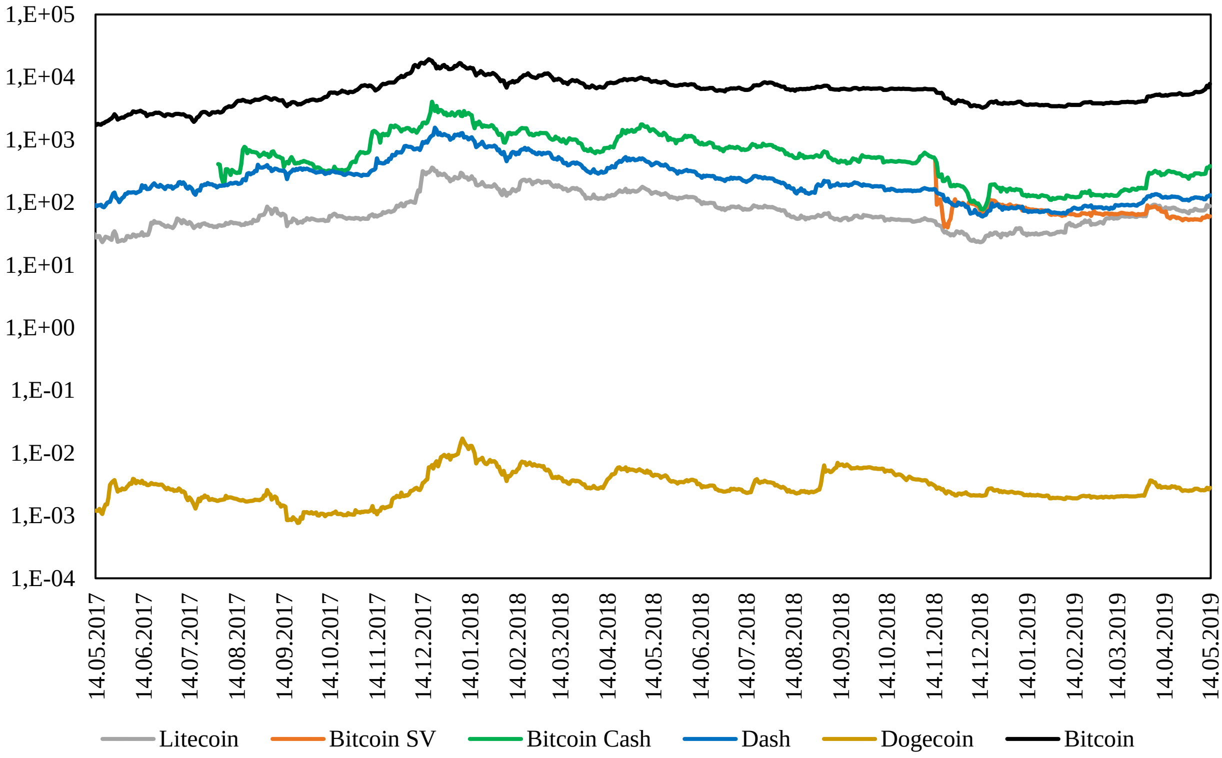


Figure 1b. The dynamics of hashrates for six blockchains

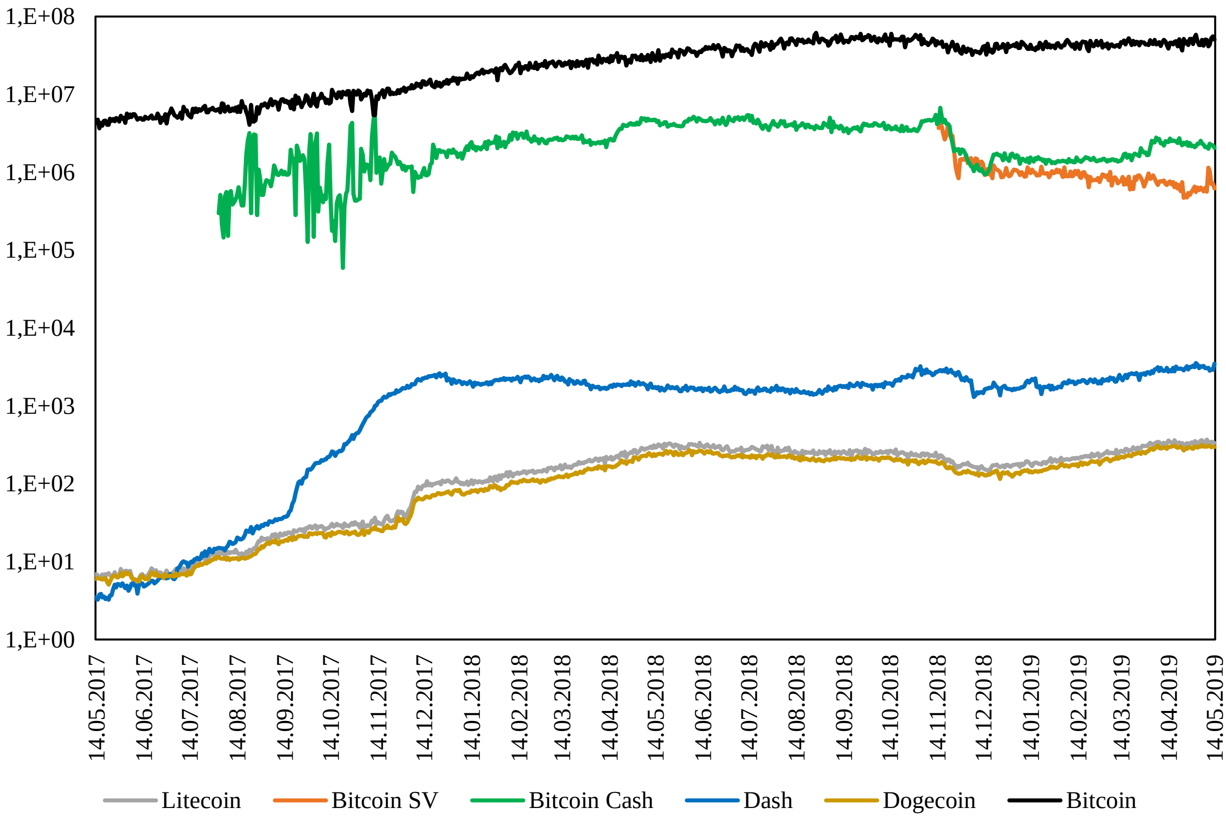
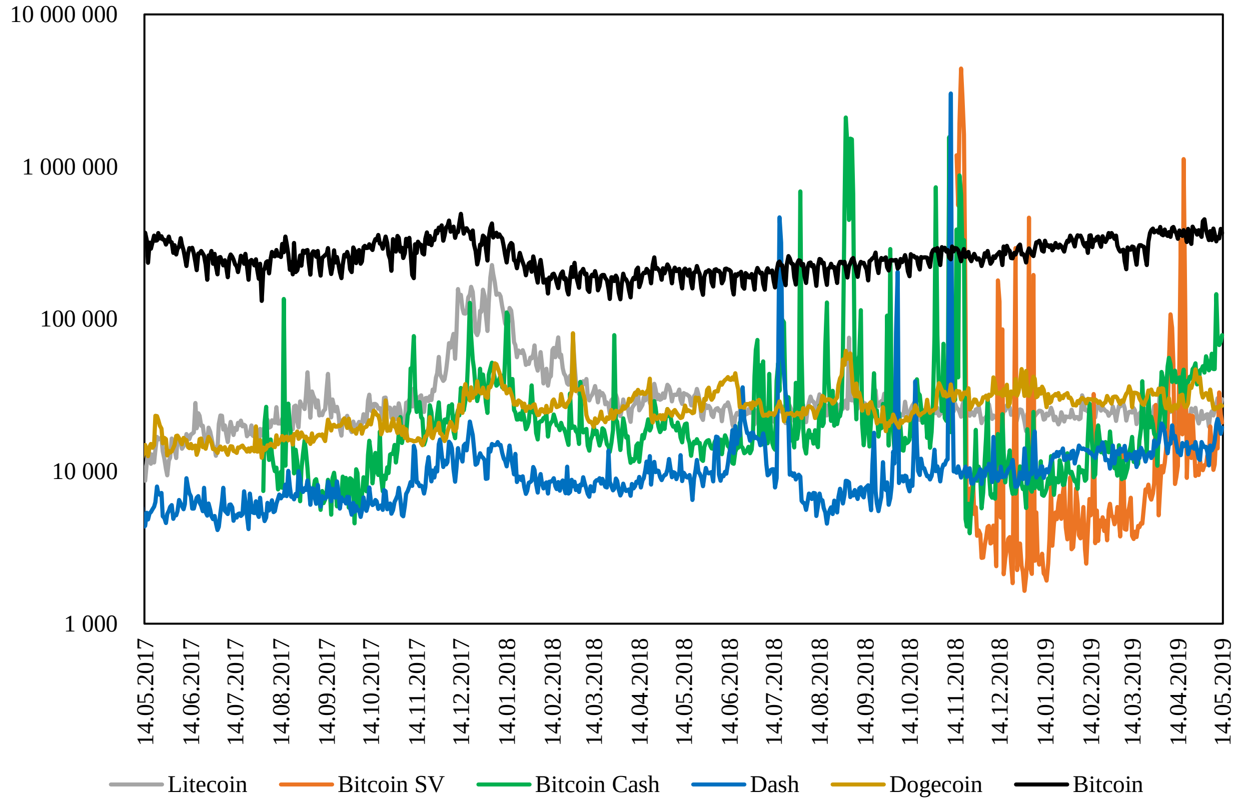


Figure 1c. The dynamics of transaction count for six blockchains



From the descriptive representation of the three essential blockchain characteristics, one can see that both hashrate and transaction count have significant variation to potentially have an economically significant impact on coin prices. Asserting that either of the two (or, perhaps, both) are meaningful for cryptocurrency value formation is somewhat intuitive from the first glance on the data: for example, Bitcoin and Bitcoin Cash are the first and the second cryptocurrency in terms of price, hashrate and transaction count. However, formal econometric estimations and rigorous testing is required to derive cause-and-affect statements regarding these blockchain aggregates.

Instrumental variable selection

To generate causal inferences about the relationship between transaction count, hashrate and coin price, a set of candidate variables has been considered, stemming from the theoretical relationship between various blockchain-specific aggregates and ratios. First, to instrument for hashrate, mining difficulty is the most obvious instrument candidate, as difficulty is tightly associated with hashrate (the greater the difficulty, the higher hashrate is required to mine the same number of blocks), but it can influence coin price only indirectly, via changes in hashrate. For five out of six sample coins (all except Bitcoin), difficulty adjusts with each block, therefore generating a potentially sufficient amount of exogenous variation to result in a powerful enough instrumental variable estimator.

For Bitcoin, however, difficulty adjusts only every 2016 blocks (approximately every two weeks), therefore it is suspected that mining difficulty might not have a strong first stage as an instrument for hashrate on daily data. Therefore, for Bitcoin, a second candidate instrument is tested, namely, the fraction of blocks mined by unknown miners (that do not represent organised mining pools). It can arguably represent the degree of "enthusiastic" mining activity by individual miners, rather than profit-seeking mining characteristic of large pools. Therefore, if the share of unknown mining is high, it could imply that mining is unprofitable, therefore resulting in a lower hashrate. Simultaneously, for the cost-based pricing framework of proof-of-work cryptocurrencies, it should be irrelevant whether the mining cost is incurred by organised mining pools or small atomistic miners, resulting in a plausible instrument candidate.

To instrument for transaction count, two transaction cost metrics – transaction fee density and fiat transaction fee – have been considered, representing exogenous drivers of adoption (as lower/higher transaction fees can influence price only via higher/lower adoption). Additionally, for Dogecoin, trading volume – an additional instrument candidate for transaction count – has been considered.

Tables 2a, 2b and 2c report first-stage regressions of endogenous regressors (hashrate and transaction count) onto respective instruments. If multiple instruments were statistically significant in first-stage estimations, the one with greater t-stat was taken. All equations were estimated using OLS with Newey-West (1987) heteroscedasticity and autocorrelation consistent covariance matrix, regressing logarithmic rate of change of the fundamental factor $\ln\frac{F_t}{F_{t-1}}$ onto the instrument $\ln\frac{IV_t}{IV_{t-1}}$ and estimating the model: $\ln\frac{F_t}{F_{t-1}} = \beta_0 + \beta_1 \ln\frac{IV_t}{IV_{t-1}} + \varepsilon_t$

Table 2a. The first stage for hashrate and transaction instruments (Bitcoin and Litecoin).

Coin	Bitcoin				Litecoin		
Endogenous variable	Hashrate		Transaction count		Hashrate	Transaction count	
Instrument candidate	Mining difficulty	**Unknown miners, %**	**Transaction fee density**	Fiat transaction fee	**Mining difficulty**	Transaction fee density	**Fiat transaction fee**
Intercept	0.0038***	0.0069***	0.0009	0.0009	0.0038**	0.0013	0.0011
	(0.0013)	*(0.0019)*	*(0.0030)*	*(0.0030)*	*(0.0016)*	*(0.0042)*	*(0.0041)*
	[2.9538]	[3.6495]	[0.2900]	[0.3008]	[2.3167]	[0.3016]	[0.2776]
Slope	-0.2213	-0.0477**	0.0811***	0.0115	-0.1129*	-0.0595***	-0.1475***
	(0.1960)	*(0.0197)*	*(0.0154)*	*(0.0160)*	*(0.0613)*	*(0.0157)*	*(0.0153)*
	[-1.1287]	[-2.4223]	[5.2711]	[0.7193]	[-1.8414]	[-3.7886]	[-9.6502]

Notes: instrument selection process for two exogenous variables (hashrate and transaction count) for Bitcoin and Litecoin. Instruments with the strongest first stage (highest t-stat with Newey-West HAC variance estimator) are **in bold** and selected for TSLS inferences. *, ** and *** denote statistical significance at 10%, 5% and 1%, respectively. Standard errors and t-statistics are reported *(in parentheses)* and [in brackets]. All endogenous variables and candidate instruments are transformed into log-differences for all estimations.

For Bitcoin, as expected, mining difficulty is not a particularly strong instrument for hashrate as it adjusts only every 2016 block, such variation being insufficient. The share of unknown miners indicator has, in turn, a rather strong first stage (significant at 5%), therefore the study proceeds to use it as an instrument for hashrate (Table 2a). In terms of transaction count instruments, transaction fee density and fiat transaction fee have a stronger first stage for Bitcoin and Litecoin, respectively, therefore, at least one of the conventional transaction cost variables can be used as instruments for the number of transactions (Table 2a).

Table 2b. The first stage for hashrate and transaction instruments (Bitcoin Cash and Bitcoin SV).

Coin	Bitcoin Cash			Bitcoin SV		
Endogenous variable	Hashrate	Transaction count		Hashrate	Transaction count	
Instrument candidate	**Mining difficulty**	Transaction fee density	**Fiat transaction fee**	**Mining difficulty**	Transaction fee density	**Fiat transaction fee**
Intercept	0.0005	0.0005	-0.0010	-0.0044	-0.0179	-0.0252
	(0.0092)	*(0.0119)*	*(0.0109)*	*(0.0056)*	*(0.0458)*	*(0.0418)*
	[0.0557]	[0.0441]	[-0.0886]	[-0.7946]	[-0.3907]	[-0.6027]
Slope	-1.5605***	-0.5884***	-0.7271***	0.6022***	-0.7999***	-0.7684***

	(0.2513)	*(0.1355)*	*(0.1103)*	*(0.0870)*	*(0.1667)*	*(0.1131)*
	[-6.2095]	[-4.3442]	[-6.5921]	[6.9191]	[-4.7974]	[-6.7963]

Notes: instrument selection process for two exogenous variables (hashrate and transaction count) for Bitcoin Cash and Bitcoin SV. Instruments with the strongest first stage (highest t-stat with Newey-West HAC variance estimator) are **in bold** and selected for TSLS inferences. *, ** and *** denote statistical significance at 10%, 5% and 1%, respectively. Standard errors and t-statistics are reported *(in parentheses)* and [in brackets]. All endogenous variables and candidate instruments are transformed into log-differences for all estimations.

Bitcoin Cash and Bitcoin SV show highly predictable results (Table 2b), with mining difficulty and fiat transaction fees having exceptionally strong first stages in terms of instrumenting hash rate and transaction count. Dash (Table 2c) follows suit, however, for Dogecoin neither transaction fee density nor fiat transaction fee is sufficiently correlated with transaction count. Here, trading volume is used as an alternative instrument, and it indeed exhibits a very strong first stage.

Table 2c. The first stage for hashrate and transaction instruments (Dash and Dogecoin).

Coin	Dash			Dogecoin			
Endogenous variable	Hashrate	Transaction count		Hashrate	Transaction count		
Instrument candidate	**Mining difficulty**	Transaction fee density	**Fiat transaction fee**	**Mining difficulty**	Transaction fee density	Fiat transaction fee	**Trading volume**
Intercept	0.0001	0.0003	0.0004	0.0001	0.0009	0.0009	0.0005
	(0.0002)	*(0.0062)*	*(0.0052)*	*(0.0001)*	*(0.0027)*	*(0.0027)*	*(0.0026)*
	[0.3335]	[0.0476]	[0.0837]	[0.9524]	[0.3533]	[0.3319]	[0.2061]
Slope	0.9958***	-0.5810***	-0.6189***	0.9801***	0.0580	0.0337	0.08157***
	(0.0065)	*(0.2034)*	*(0.1399)*	*(0.0063)*	*(0.0460)*	*(0.0374)*	*(0.0096)*
	[153.0054]	[-2.8558]	[-4.4227]	[156.2124]	[1.2616]	[0.9022]	[8.4997]

Notes: instrument selection process for two exogenous variables (hashrate and transaction count) for Dash and Dogecoin. Instruments with the strongest first stage (highest t-stat with Newey-West HAC variance estimator) are **in bold** and selected for TSLS inferences. *, ** and *** denote statistical significance at 10%, 5% and 1%, respectively. Standard errors and t-statistics are reported *(in parentheses)* and [in brackets]. All endogenous variables and candidate instruments are transformed into log-differences for all estimations.

Overall, the selected instruments for hashrate and transaction count for six sample proof-of-work coins are outlined in Table 3 below.

Table 3. Selected instrumental variables

Coin	Hashrate	Transaction count
Bitcoin	% unknown miners	transaction fee density
Litecoin	mining difficulty	fiat transaction fee
Bitcoin Cash	mining difficulty	fiat transaction fee
Bitcoin SV	mining difficulty	fiat transaction fee
Dash	mining difficulty	fiat transaction fee

Dogecoin	mining difficulty	trading volume

Estimation technique

When the instrumental variables have been selected, a set of econometric equations regressing log-returns of six proof-of-work coins onto logarithmic differences in hashrate and/or transaction count is estimated both using OLS and TSLS, reflecting Young's (2017) recommendations. For each such pair of OLS/TSLS estimations, joint regressor endogeneity is tested using the Durbin-Wu-Hausman procedure of determining the significance of the difference between J-stats (Nakamura and Nakamura, 1981). Furthermore, weak instruments are identified using Cragg-Donald (Cragg and Donald, 1993) F-test. If Cragg-Donald F-stat exceeds the 10% threshold (meaning that the possible bias of TSLS estimators due to insufficiently strong instruments is at most 10%), the instrumental variable cannot be considered weak. All standard errors are estimated using Newey-West (Newey and West, 1987) heteroscedasticity and autocorrelation consistent covariance matrix.

If the instruments are proven to be weak (low Cragg-Donald F-stat) or if the original regressors (hashrate and transaction count) are shown to be exogenous (insignificant difference in J-stats), then the hypothesis regarding the relevance of adoption-based and cost-based valuation models is tested using the OLS estimators. If, on the other hand, instruments cannot be regarded as week and IV estimator is significantly different from the OLS estimator simultaneously, the results of the TSLS model are interpreted in the context of hypothesis testing.

Findings and Discussion

The study has estimated six econometric models (the impact of hashrate, transaction count and both with OLS and TSLS) for each of the six proof-of-work coins (Bitcoin, Litecoin, Bitcoin

Cash, Bitcoin SV, Dash and Dogecoin) individually. The results are presented in Tables 4a-f, respectively.

Table 4a. Bitcoin value formation.

Coin	Bitcoin					
Model	Hashrate		Transaction count		Both	
Method	OLS	TSLS	OLS	TSLS	OLS	TSLS
Constant	0.0018*	0.0008	0.0018*	0.0017*	0.0018*	-0.0004
	(0.0009)	*(0.0015)*	*(0.0009)*	*(0.0009)*	*(0.0009)*	*(0.0025)*
	[1.9122]	[0.0542]	[1.9047]	[1.8872]	[1.9097]	[-0.1758]
Hashrate	-0.0051	0.5165			-0.0039	0.4625
	(0.0059)	*(0.3250)*			*(0.0060)*	*(0.4491)*
	[-0.8721]	[1.5894]			[-0.6511]	[1.0298]
Transaction count			-0.0051	0.0448	-0.0039	0.7352
			(0.0059)	*(0.0524)*	*(0.0061)*	*(0.6908)*
			[-0.8552]	[0.8550]	[-0.6457]	[1.0604]
Endogeneity test	4.8389**		1.0314		5.4602*	
	0.0278		*0.3098*		*0.0652*	
Cragg-Donald F-stat	1.2628		**27.7849**		0.1788	

Notes: all models estimated using standard OLS and TSLS with pre-selected instruments using a HAC covariance matrix. *, ** and *** denote statistical significance at 10%, 5% and 1%, respectively. Standard errors and t-statistics are reported *(in parentheses)* and [in brackets]. Endogeneity tests (differences in J-stats) with respective p-values *in italics* presented below main estimation results. Cragg-Donald F-stats that pass the 10% threshold are **in bold**.

For Bitcoin, both OLS and TSLS estimators of hashrate and transaction count impact on returns is statistically insignificant. These regressors are shown to be exogenous in two out of three models, while the share of unknown miners is shown to be a relatively weak instrument for hashrate. Transaction fee density, however, is a very strong instrument for transaction count, albeit the transaction count regressor in this model is shown to be exogenous, regardless. Overall, the instrument selected are far from ideal in case of Bitcoin, however, there is no evidence to support either cost-based (Hayes' marginal cost of mining) or adoption-based (Metcalfe's law) frameworks for Bitcoin valuation, as both OLS and TSLS estimators are insignificant in all cases.

Table 4b. Litecoin value formation.

Coin	Litecoin					
Model	Hashrate		Transaction count		Both	
Method	OLS	TSLS	OLS	TSLS	OLS	TSLS
Constant	0.0017	0.0025	0.0018	0.0022	0.0017	0.0025

	(0.2616)	*(0.0023)*	*(0.0015)*	*(0.0018)*	*(0.0015)*	*(0.0030)*
	[1.1229]	[1.1065]	[1.1984]	[1.2111]	[1.1223]	[0.8430]
Hashrate	0.0419**	-0.2163			0.0429**	-0.1059
	(0.0200)	*(0.4891)*			*(0.0199)*	*(0.6352)*
	[2.0989]	[-0.4421]			[2.1530]	[-0.1668]
Transaction count			-0.0114	-0.2779***	-0.0119	-0.2746***
			(0.0083)	*(0.0901)*	*(0.0083)*	*(0.0884)*
			[-1.3761]	[-3.0841]	[-1.4450]	[-3.1081]
Endogeneity test	0.2889		57.8122***		58.4219***	
	0.5909		*0.0000*		*0.0000*	
Cragg-Donald F-stat	3.3910		**93.1267**		1.6504	

Notes: all models estimated using standard OLS and TSLS with pre-selected instruments using a HAC covariance matrix. *, ** and *** denote statistical significance at 10%, 5% and 1%, respectively. Standard errors and t-statistics are reported *(in parentheses)* and [in brackets]. Endogeneity tests (differences in J-stats) with respective p-values *in italics* presented below main estimation results. Cragg-Donald F-stats that pass the 10% threshold are **in bold**.

Litecoin initially shows some support for a cost-based pricing model in OLS estimation, as hashrate has a positive and significant (at 5%) impact on log-returns both individually and when controlled for transaction count. In a single-factor model with hashrate, the TSLS estimator is insignificant, however this result alone cannot be considered enough to reject the validity of the cost-based model for Litecoin, as the instrument is not sufficiently strong in this case and, more importantly, the original regressor is shown to be exogenous. Nevertheless, in the TSLS model where both hashrate and transaction cost are included, hashrate is still insignificant, while the regressors are shown to be exogenous. Therefore, Litecoin has produced mixed and somewhat inconclusive results regarding Hayes' (2017, 2019) cost-based pricing model. With regards to adoption-based model, however, the findings are extremely consistent – fiat transaction fee is a strong instrument for transaction count, transaction count alone is proven to be an endogenous regressor at extremely high levels of confidence, and the number of transactions factor, remaining insignificant in OLS estimations, consistently turns negative and highly (at 1%) significant in TSLS models. This is sufficient evidence to reject the validity of Metcalfe's law models (expecting a positive transaction-price relationship) in application to Litecoin.

Table 4c. Bitcoin Cash value formation.

Coin	Bitcoin Cash

Model Method	Hashrate OLS	 TSLS	Transaction count OLS	 TSLS	Both OLS	 TSLS
Constant	-0.0002 *(0.0038)* [-0.0470]	0.0001 *(0.0040)* [0.0161]	-0.0001 *(0.0038)* [-0.0297]	0.0000 *(0.0039)* [0.0078]	-0.0002 *(0.0038)* [-0.0469]	0.0002 *(0.0041)* [0.0436]
Hashrate	0.0229* *(0.0138)* [1.6591]	-0.0581** *(0.0286)* [-2.0337]			0.0229* *(0.0138)* [1.6657]	-0.0499* *(0.0284)* [-1.7572]
Transaction count			0.0011 *(0.0071)* [0.1564]	-0.0384*** *(0.0117)* [-3.2988]	-0.0003 *(0.0068)* [-0.0379]	-0.0383*** *(0.0118)* [-3.2413]
Endogeneity test	54.0084*** *0.0000*		43.7898*** *0.0000*		93.0107*** *0.0000*	
Cragg-Donald F-stat	**427.4585**		**583.9237**		**213.6075**	

Notes: all models estimated using standard OLS and TSLS with pre-selected instruments using a HAC covariance matrix. *, ** and *** denote statistical significance at 10%, 5% and 1%, respectively. Standard errors and t-statistics are reported *(in parentheses)* and [in brackets]. Endogeneity tests (differences in J-stats) with respective p-values *in italics* presented below main estimation results. Cragg-Donald F-stats that pass the 10% threshold are **in bold**.

Bitcoin Cash can be regarded as a textbook case of inconsistent OLS estimators in the presence of endogeneity. While similar to Litecoin, Bitcoin Cash shows a robust positive relationship between returns and hashrate (significant at 10%) in case of simple OLS, the estimator remains significant, but changes sign in IV regressions. This observation cannot be explained as an artefact of weak instruments, as Cragg-Donald F-stats are extremely high and Durbin-Wu-Hausman test shows that hashrate is indeed an endogenous regressor. For transaction count, similarly endogenous (as evidenced by the difference in J-stats statistically significant at 1%) though insignificant OLS regressors turn negative and significant in TSLS estimations. Hence, both cost-based and adoption-based valuation models can be decidedly rejected for Bitcoin Cash.

Table 4d. Bitcoin SV value formation.

Coin	Bitcoin SV					
Model	Hashrate		Transaction count		Both	
Method	OLS	TSLS	OLS	TSLS	OLS	TSLS
Constant	-0.0130 *(0.0122)* [-1.0612]	-0.0129 *(0.0112)* [-1.1498]	-0.0114 *(0.0117)* [-0.9712]	-0.0121 *(0.0123)* [-0.9872]	-0.0128 *(0.0121)* [-1.0531]	-0.0133 *(0.0117)* [-1.1360]
Hashrate	-0.1376 *(0.0916)* [-1.5014]	-0.1292 *(0.1843)* [-0.7013]			-0.1379 *(0.0909)* [-1.5174]	-0.1282 *(0.1900)* [-0.6748]
Transaction count			0.0103 *(0.0073)* [1.4167]	-0.0213 *(0.0183)* [-1.1654]	0.0104 *(0.0071)* [1.4558]	-0.0184 *(0.0180)* [-1.0191]

Endogeneity test	0.0041	15.2765***	13.1587***
	0.9487	*0.0001*	*0.0014*
Cragg-Donald F-stat	**46.7888**	**215.6563**	**22.0414**

Notes: all models estimated using standard OLS and TSLS with pre-selected instruments using a HAC covariance matrix. *, ** and *** denote statistical significance at 10%, 5% and 1%, respectively. Standard errors and t-statistics are reported *(in parentheses)* and [in brackets]. Endogeneity tests (differences in J-stats) with respective p-values *in italics* presented below main estimation results. Cragg-Donald F-stats that pass the 10% threshold are **in bold**.

Bitcoin SV, perhaps due to the relative youth of the coin and respective levels of idiosyncratic risk, shows mostly insignificant results. Hashrate is shown to have no significant impact on price and the estimator value is similarly negative in both models. According to the Durbin-Wu-Hausman test, hashrate can be considered exogenous for Bitcoin SV valuation, therefore insignificant OLS estimates can be accepted as consistent. Transaction count is shown to contribute positively, albeit insignificantly, to Bitcoin SV return in OLS models, however, the relationship flips its sign in IV regressions, the endogeneity test reinforcing the significant difference between estimators in these two methods. In all cases, the instruments are evidenced to be of sufficient strength. Overall, the lack of significant results allows the study to reject both simplistic valuation models for Bitcoin SV.

Table 4e. Dash value formation.

Coin	Dash					
Model	Hashrate		Transaction count		Both	
Method	OLS	TSLS	OLS	TSLS	OLS	TSLS
Constant	-0.0001	-0.0002	0.0005	0.0006	-0.0001	0.0001
	(0.0023)	*(0.0023)*	*(0.0023)*	*(0.0024)*	*(0.0023)*	*(0.0024)*
	[-0.0551]	[-0.0717]	[0.2171]	[0.2479]	[-0.0490]	[0.0003]
Hashrate	0.0646*	0.0686*			0.0642*	0.0619
	(0.0358)	*(0.0363)*			*(0.0358)*	*(0.0376)*
	[1.8046]	[1.8881]			[1.7911]	[1.6438]
Transaction count			-0.0052	-0.0533**	-0.0050	-0.0526**
			(0.0042)	*(0.0252)*	*(0.0044)*	*(0.0253)*
			[-1.2405]	[-2.1112]	[-1.1425]	[-2.0792]
Endogeneity test	0.5272		47.5775***		47.3067***	
	0.4678		*0.0000*		*0.0000*	
Cragg-Donald F-stat	**24518.84**		**712.9432**		**355.4682**	

Notes: all models estimated using standard OLS and TSLS with pre-selected instruments using a HAC covariance matrix. *, ** and *** denote statistical significance at 10%, 5% and 1%, respectively. Standard errors and t-statistics are reported *(in parentheses)* and [in brackets]. Endogeneity tests (differences in J-stats) with respective p-values *in italics* presented below main estimation results. Cragg-Donald F-stats that pass the 10% threshold are **in bold**.

Dash is the only case where some inconclusive evidence has been found in support of the cost-based model. OLS estimator is positive and significant (at 10%), and the single-factor model shows that hashrate can be treated as an exogenous regressor. However, in the TSLS two-factor model (including both hashrate and transaction count), where joint regressor endogeneity is evidenced by the statistically significant (at 1%) difference in J-stats, hashrate becomes marginally insignificant. Of course, analogously to the case of Litecoin, these findings are not enough to either verify or falsify the cost-pricing valuation framework for Dash. With regards to the adoption-based model, the results are once again much more evident: statistically insignificant OLS estimators are substantially different (according to Durbin-Wu-Hausman endogeneity test) to statistically significant (at 5%) and negative TSLS estimators. As all instruments in all models are proven to be strong, the adoption-based pricing model can be certainly rejected for Dash.

Table 4f. Dogecoin value formation

Coin	Dogecoin					
Model	Hashrate		Transaction count		Both	
Method	OLS	TSLS	OLS	TSLS	OLS	TSLS
Constant	0.0012	0.0012	0.0018	0.0020	0.0013	0.0003
	(0.0033)	*(0.0033)*	*(0.0033)*	*(0.0034)*	*(0.0033)*	*(0.0033)*
	[0.3737]	[0.3535]	[0.5456]	[0.5708]	[0.3936]	[0.0964]
Hashrate	0.0981	0.1102			0.0904	0.0738
	(0.0622)	*(0.0634)*			*(0.0617)*	*(0.0660)*
	[1.5778]	[1.7389]			[1.4664]	[1.1173]
Transaction count			-0.0429*	-0.1881**	-0.0394	-0.1853**
			(0.0251)	*(0.0860)*	*(0.0248)*	*(0.0864)*
			[-1.7083]	[-2.1876]	[-1.5850]	[-2.1452]
Endogeneity test	1.6173		3.5444*		5.2452*	
	0.2035		*0.0597*		*0.0726*	
Cragg-Donald F-stat	**29150.73**		**89.6884**		**44.4427**	

Notes: all models estimated using standard OLS and TSLS with pre-selected instruments using a HAC covariance matrix. *, ** and *** denote statistical significance at 10%, 5% and 1%, respectively. Standard errors and t-statistics are reported *(in parentheses)* and [in brackets]. Endogeneity tests (differences in J-stats) with respective p-values *in italics* presented below main estimation results. Cragg-Donald F-stats that pass the 10% threshold are **in bold**.

Dogecoin is a special case as it involves sufficiently strong instruments and marginally significant evidence of regressor endogeneity (insignificant for hashrate single-factor model and significant only at 10% in two other cases). Regardless, there are no positive and significant results for either hashrate or transaction count, transaction count estimator being negative and significant (at 5%) in both TSLS models. The findings are therefore allowing the study to reject both cost-based and adoption-based model for Dogecoin.

Overall, the results of the econometric estimations overwhelmingly suggest that neither cost-pricing nor Metcalfe's law models are robust and useful valuation heuristics for proof-of-work cryptocurrencies. For all six coins, the adoption-based model has been decidedly rejected, while the cost-based model has been rejected with certainty for four out of six coins, the other two coins showing inconclusive results. It can be inferred that statistically significant results related to adoption-based models in the previous literature (Alabi, 2017; Peterson, 2018; Van Vliet, 2018; Pele and Pele, 2019) are spurious due to autocorrelation, while reported evidence supporting cost-based models (Hayes, 2017, 2019) is inconsistent due to regressor endogeneity, i.e. the relationship between network hashrate and coin price being not unidirectional.

Conclusion

This study has rigorously tested two most frequently used fundamental valuation heuristics for cryptocurrencies – cost-based pricing associated with network hashrate (Hayes, 2017, 2019) and adoption-based pricing based on Metcalfe's law and transaction count (Alabi, 2017; Peterson, 2018; Van Vliet, 2018; Pele and Pele, 2019) – against blockchain data for six proof-of-work cryptocurrencies (Bitcoin, Litecoin, Bitcoin Cash, Bitcoin SV, Dash and Dogecoin) using causal inferences from instrumental variables estimators.

Instrumental variable approach is shown to be both technically applicable and practically relevant to fundamental analysis of cryptocurrencies as, unlike for stocks, major fundamental indicators of blockchains such as hashrate and transaction count, cannot be treated as exogenous as they are themselves responding to changing coin prices and adjusting with each block, new information instantly becoming publically available.

For various cryptocurrencies, different hashrate and transaction count instruments are shown to have the strongest first stage. For blockchains with continuously adjusting difficulty, changes in difficulty are sufficiently strong instruments for changes in hashrate, while for those where difficulty adjusts periodically (e.g. in Bitcoin blockchain, where it changes only every 2016 blocks or, approximately, every two weeks) another instrument, such as the share of unknown miners, might be more applicable. To instrument for the number of transaction dynamics, either transaction fee density, fiat transaction fees or trading volume can be utilised in various cases, with fiat transaction fee being the most universal.

The instrumental variable approach and causal inferences obtained from respective IV estimators suggest that most of the statistically significant positive results with regards to the relationship between coin price and hashrate or coin price and transaction count are either spurious due to serial correlation (predominantly in case of Metcalfe's law models) or inconsistent due to endogeneity (mostly in case of cost-based pricing models). The study consistently failed to verify the predictions of either of the two models, the adoption-based model being decidedly rejected for all six cryptocurrencies, while the cost-based model being rejected in four out of six cases and having inconclusive results in other two.

The study has shown that simplistic single-factor valuation models and frameworks for proof-of-work cryptocurrencies are not sufficient for adequate fundamental analysis and that more advanced developments in the field, perhaps simultaneous equilibrium-based models, are necessary. Hence, discovering theoretically plausible and empirically consistent sources of cryptocurrency value generation is essential for cryptocurrency researchers, investors and blockchain enthusiasts alike. Furthermore, the study has shown the importance of econometric rigour in empirical cryptocurrency research, showing that some potentially spurious results in existing literature can be solely attributable to inadequate methodological design. Finally, it has provided the methodological basis for instrumental variable estimations and causal inferences in the field, suggesting some empirically robust instrument candidates for frequently used blockchain-related fundamentals such as network hashrate and transaction count.

Further research in the field might apply a similar instrumental variable framework to study other aspects of cryptocurrency economics, such as supply and demand on the transaction fee market, formally testing existing theoretical models of transaction fee determination. Furthermore, the system of simultaneous equations can be utilised in the future to test the supply and demand model of cryptocurrency price if a sufficient supply curve-shifter is developed.

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