Assets on the blockchain: an empirical study of Tokenomics

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Abstract

Digital tokens linked to financial and economic ventures may have multiple functions and uses. In this work, we examine the relationship between various token functions and the market price of the corresponding token. We consider 86 venture related blockchain tokens, and develop the analysis through a stepwise testing of four hypotheses using panel ordinary least squares with cluster-robust standard errors. We find that token functions are statistically significant in relation to token prices. In the absence of an established legal framework, we argue that our results complements recent regulatory actions identifying tokens to be investment contracts in a common venture.

JEL G32 O31

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Highlights

- Bitcoin is a provably scarce digital asset used to facilitate payments.
- Ethereum has both a payment asset and smart contract utility.
- Other blockchain tokens promise income or value from a platform.
- These structures are delineating novel economic links between a project and a token.
- Token function can impact token price.

1. Introduction

Sales of blockchain tokens, often referred to as initial coin offerings (ICOs), raised $5.3 billion in 2017 (Adhami et al., 2018). These funds are testament to the financial significance of crypto tokens. The token market capitalizations of a subset of these tokens, used in this study, are shown in Figure 1 to help visualize their size and recent performance. Following the seminal work of Nakamoto (2009), researchers have built a solid understanding of the underlying technology (Yli-Huuomo et al., 2016; Narayanan et al., 2016). The information layer of the Bitcoin blockchain consists

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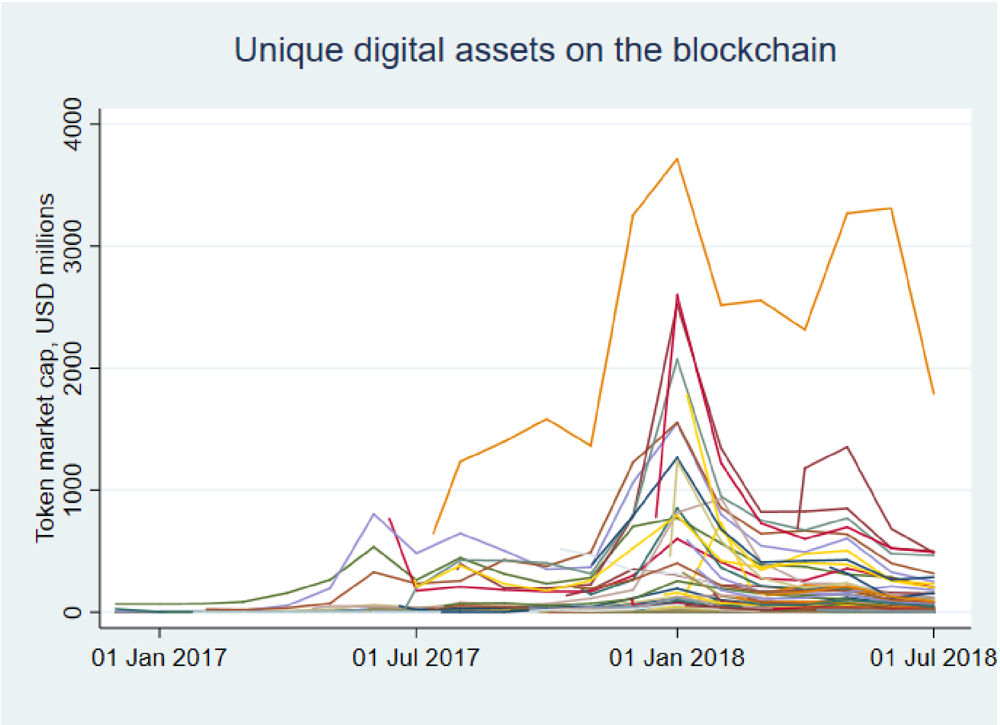

Figure 1: Market capitalization of study sample of blockchain tokens

of blocks of transaction data linked together, such that an attempt to change one transaction, requires changing all those chained after it. This is the censorship resistant record. Any processor (aka miner), authentic or adversarial, can compete for the right to add a block to the chain, and garner a reward of cryptocurrency, by solving a computing intensive cryptographic puzzle. Miners are able to enter freely and the system shows no bias between existing miners and new entrants. This is the mechanism behind the system decentralization, with the longest chain of proofs determining consensus around the state of the world the blockchain describes. Public keys, known as addresses, link transactions with pseudonymous address owners (who control their assets via private cryptographic keys). Together, this web of computer science, game theory and cryptography delivers the provably scare digital asset of Bitcoin. In a key paper connecting the technology to the economics of blockchain, Cong and He (2019) provides a formal proof of how a blockchain based consensus, that includes smart contract based prices contingent on delivery, can support new entrants. In their framework, new entrants signal quality by trustlessly guaranteeing buyers compensation if the product fails, explicitly enlarging the contract space.

Bitcoin and Ether are cryptotokens native to the Bitcoin blockchain and the Ethereum blockchain respectively. Buterin (2013)'s Ethereum platform formalized smart contracts on a blockchain. Smart contracts are shared computer objects that can manipulate state e.g. token balances. Smart contracts enable many contingent actions, including the issuance and trading of non-native tokens by third parties on blockchains such as Ethereum in under 30 minutes.[1]

[1]https://news.bitcoin.com/launching-an-ico-token-on-ethereum-in-less-than-thirty-minutes/

Bartoletti and Pompianu (2017) surveys various smart contract platforms and highlights the diminished barriers to issuing tradeable digital tokens.

These digital tokens may claim a link to a real world venture. Cong and He (2019), Catalini and Gans (2018) and Canidio (2018) connect blockchain consensus with new token structures and economic models. One functional category of this is the utility token, which is exchangeable for a service provided by the venture. Catalini and Gans (2018) use economic proofs to show how such a utility token, limited in quantity, and the sole medium of exchange, can appropriate the returns to a given platform. Under these conditions, the token price can appreciate in proportion to a rise in demand for the service on the platform. They note how these platforms are typically open source software protocols that equate to shared infrastructure among ecosystem participants. They use this framework to contrast token fund raising and venture capital. Importantly, equity investment offers the returns on all current and future projects of a firm, whereas token investment is solely in the current platform. These tokens therefore represent a more circumscribed package of entrepreneurship, value creation and value capture than an equity. Canidio (2018) addresses the possibility of exit scams, where an issuer steals the funds raised, with retained token holdings and mixed strategies. In Chod and Lyandres (2018), retained token holdings are one way for issuers to address asymmetric information.

However, despite the scope and scale of cryptoassets, there is little understanding of what a token holder has acquired in practice. This is partly because unregulated blockchain based tokens rarely include any legal obligations. Users are being asked to fund a business, which raises the question: what they are receiving relative to what they are promised? Cohney et al. (2019) explores this by comparing marketing promises with smart contract code. Nevertheless most empirical work on blockchain tokens so far have been focused on cryptocurrency prices (Briere et al., 2015; Brandvold et al., 2015; Bouri et al., 2017; Lo, 2017; Pieters and Vivanco, 2017) or ICO success and size (Benedetti and Kostovetsky, 2018; Amsden and Schweizer, 2018; Howell et al., 2018; Adhami et al., 2018). Overall the academic literature is responding to this new capital structure of a venture, yet so far lacks evidence that its newest components authentically link project and token. The latter becomes the first objective of our analysis: to investigate the linkage between a project that has a value, and a token that has a price. The second objective is to investigate differences between functional types of blockchain tokens. A result that shows token type impacts prices imply that legislators and policy makers should create a framework that differentiates between different types of tokens. A result that shows no difference would imply that regulators can focus on ICOs as a broad category of venture capital funding, and pay less attention to the nature of the token.

We develop our paper through a stepwise approach testing four hypotheses that investigate this novel link between venture and price. We start by parsing out the relationships between our sample blockchain tokens and two major cryptocurrencies, then by isolating the effect of different token functions, token features and token distribution characteristics highlighted in the literature (Figure 2). Ultimately our examination of the impact of common token structures on token price is intended to contribute to the wider question of what can these new tokens embody and connect, and touches on the possibility of new forms of information discovery.

The cryptotoken space is dominated by two specific cryptocurrencies. Bitcoin is the primary means of buying and

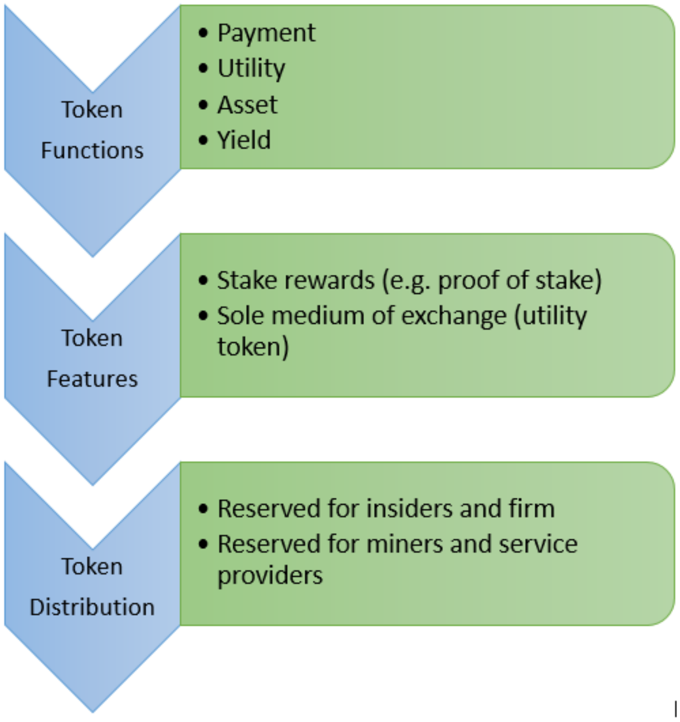

Figure 2: Token characteristics addressed in the analysis

selling tokens, while Ethereum smart contracts are often the technological basis of many of these tokens, and sometimes a fee component of the application business an ICO is building. Bitcoin and Ether are also the main currencies used in funding ICOs. Both underpin distribution of tokens following a token generation event. For example, ERC-20 is the technical standard for issuing third party tokens on the Ethereum platform. Therefore buying an ERC-20 token with Ether occurs on a single blockchain platform, and is the easiest way to engage in such a transaction. Buying an ERC-20 token with other cryptocurrencies requires additional steps or coding, because the transaction crosses between two blockchains. Our first hypothesis emerges from the importance of these two cryptocurrencies.

- H1: "Price changes in Bitcoin and Ether cause price changes in ICO tokens."

In our analysis we assume a direct relationship between Bitcoin, Ether and ICO prices. We then move on to our core hypothesis, that the functions that constitute a token create an economic link between a project that has a value, with a token that has a price. The idea that price and value can be separate is commonplace in the finance literature, though the definition of intrinsic value varies with the object of study (Lee et al., 1999; Froot and Ramadorai, 2005).

- H2: "Token function impacts the relationship between an underlying business value and its market price."

Our paper classifies the sample of tokens according to the token's functionality. We look specifically for the influence of functional dummies on a token's trading price. The four key functions we study are: (1) payment, (2) utility, (3) asset and (4) yield. We distinguish between share of profits type yields, and proof of stake blockchain type rewards (that distribute tokens to nodes that participate in consensus generation). One difference between the two is that the former is paid in a separate currency out of platform income (e.g. a dividend in Ether), while staking is in the token currently held, and numerically dilutive. Because of this, we consider share of profits to be a function and staking to be a feature. For reference, yield only tokens do exist in the dataset, but staking is typically associated with other functionalities as it reflects an underlying technical choice e.g. a proof of stake blockchain variant. There are other ways to interpret the promise of staking, including the potential elimination of platform mining costs and lower electricity consumption. However we are wary of categorizing a promise of stake rewards as usage of proof of stake technology (versus proof of work), because sampled project tokens typically begin trading on a proof of work blockchain platform such as Ethereum.

With respect to a token being the sole medium of exchange on a platform, in theory it is necessary for a utility token to adhere to this in order to appropriate the benefits of the platform (Catalini and Gans, 2018). We collect data on whether or not a utility token is intended as the sole medium of exchange for the related platform and test for any relationship between this factor and the token's trading price. The features of staking and sole medium of exchange are bundled together in our third hypothesis.

- H3: "Token's promising the characteristics of stake rewards and sole medium of exchange on a platform, trade at a higher price."

Designating a token as the sole medium of exchange does not always resonate with investors. A prominent example of this is how Basic Attention Token (BAT) has faced calls to make payments in US Dollars or Bitcoin instead of BAT tokens [2]. Sole medium of exchange requirements may slow wider adoption, as changing in and out of the utility coin becomes a barrier to use.

Our final hypothesis revolves around the criticality of token distribution at the time of ICO. This focuses on the split in economics between investors, relative to insiders and future service providers. These token distribution decisions are likely endogenous, and operate in two contrasting ways. It is plausible that the better the project, the higher the share of tokens reserved for insiders - and therefore signals quality to outsiders. Conversely, an increase in either of these reserved token categories decrease the share of platform economics received by funders. Our framework enables us to test for which of these effects dominate in terms of price.

- H4: "ICOs with a higher proportion of outstanding tokens reserved for the token issuer, or a lower proportion of tokens reserved for mining, trade at a higher price."

[2] https://blog.goodaudience.com/basic-attention-token-bat-fails-to-live-up-to-its-claims-7b1a91d46b01

We use the proportion of tokens reserved for founders / team members / company controlled foundation, or reserved for mining, future marketing or future partnership building.

The paper is structured as follows. Section 2 explores different blockchain token functions and features. Section 3 addresses the data, including an examination of selection biases. Section 4 describes our empirical methodology. Section 5 presents our results, including a discussion that compares our results with our hypotheses. We close with a conclusion.

2. Token classification

Blockchain token structures are non-standardized. The potentially unique economics of each token are not based on legal rights, but on their promises (e.g. claims and features) and abilities (functions). Consequently these features and functions may create economic relationships extending from the underlying business to the digital token. In contrast, a share in IBM and a share in Coca Cola are the same legal and financial claim upon different businesses, and contain legally enforceable primitive financial and managerial rights (Myers, 2000). As it stands there is no comparable class of attributes that groups all ICO tokens.

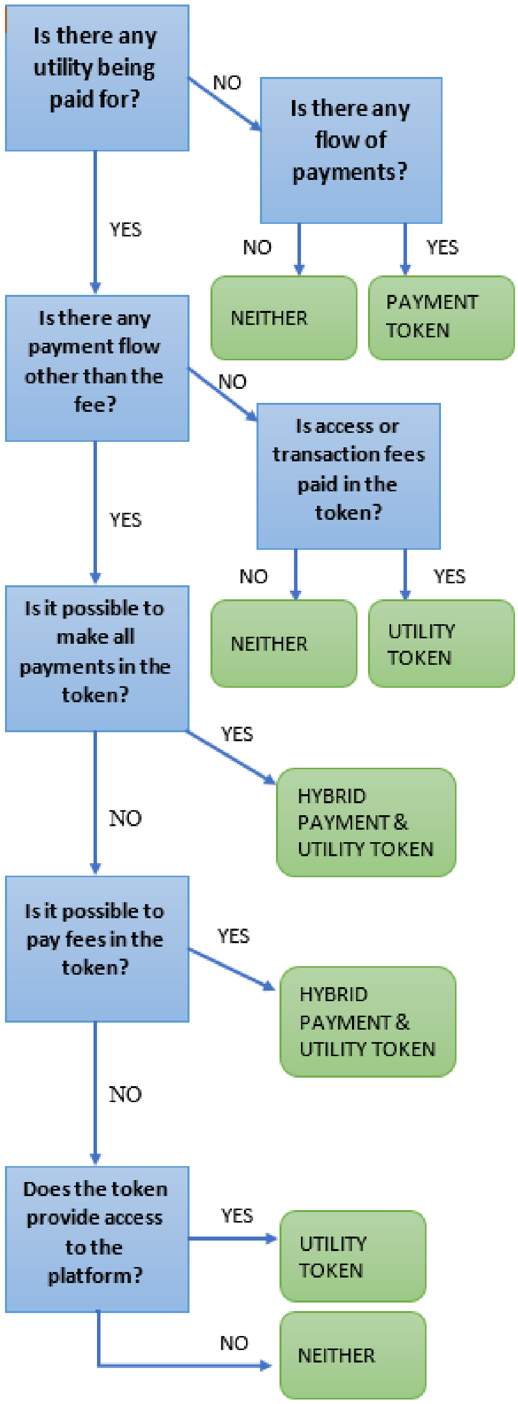

Figure 3: Characterization of token as payment or utility

The Bitcoin blockchain is a payment protocol, a set of rules and conventions for the movement of value between network addresses. Narayanan and Clark (2017) observe the simplicity of leveraging a secure ledger to create a digital payment system. But tokens can have other uses. For this paper, our starting point is the Swiss financial regulator FINMA (2018)'s identification of financial blockchain tokens into three functional categories: payment tokens, utility tokens, and asset tokens. These categories are not mutually exclusive - a token can be designed to perform all three functions.

Payment tokens are a means of value transfer, spanning cryptocurrencies like Bitcoin, to industry specific ICO tokens e.g. DragonChain that seeks to reduce frictions within the casino industry. FINMA (2018) defines a utility token as intended to provide access digitally to an application or service, by means of a blockchain-based infrastructure. This may include the ability to exchange the token for the service. The Ethereum blockchain's utility is its smart contracts, that enable the distributed processing of permissionless computer code in a predictable way. Consequently, we define Ether as a payment and utility token, with smart contract execution, network fees, and the ability to transfer value outside of fees. The sample of blockchain token prices that we test, as a dependent variable, includes three cryptocurrency like payment and utility tokens (Tezos, Viacoin, and Wanchain). We note that we do not make the distinction, sometimes seen in computer science, that a blockchain Coin is one that trades on its own infrastructure, and that a blockchain Token is one that trades on third party infrastructure.

FINMA's definition of an asset token includes attempts to bind physical or digital assets to a digital blockchain token, and promises to share profits. Our framework differs from FINMA's model, in that we separate the asset category into two functions: (1) tokens linked to a physical or digital asset e.g. silver or collective crypto investment funds, and (2) tokens that promise to pay a share of profit or revenue. We refer to the former as the functionality of asset, and the latter as the functionality of yield.

Both asset and yield functions are binary in nature, and therefore straightforward to categorize. However it is necessary to formalize the identification of payment and utility functionality. This is illustrated in the flow diagram in Figure 3. The key criteria within the proposed framework for definition as a payment token is the presence of a payment flow other than the fee, and the ability to use the token to address either the flow or the fee. The flow diagram divides the payment ability of the token into (1) transacting the payment flow and (2) paying the fee, not because the result is different, but to highlight that many tokens make this distinction in usage. A payment flow opportunity addressed by a platform, but not payable in the associated token, might not be designated a payment token. Our sample does not include any payment only cryptocurrencies like Bitcoin, rather they are primarily industry or purpose specific payment tokens.

In our sample, the most common reason that a token is neither a payment nor utility token is because it is an asset token, linked either to a portfolio of cryptoassets, some off-chain real world asset like silver, or a share of platform profits. For example, Crypto20's token C20 is a tokenized crypto investment fund. An example of a utility token with no payment flow is the WePower WPR token. Its objective is to streamline the presale of renewable energy (facilitate project funding), with WPR receiving a share of "donated" power. WPR is not considered a payment token as separate energy tokens are sold by plant or projects on the WePower platform. This is in contrast to another energy platform token, Suncontract SNC, which does not use a secondary token in this way. Each SNC token is intended to be associated with a quantity of electricity.

Our framework categorizes non-platform businesses as a utility token. For example Hedge Token HDG was a crypto financial services provider, selling its own products and services via its token. HDG has now migrated to the Blocktrade token BTT, which is a crypto exchange, and therefore within our framework it is now a hybrid payment and utility token, with a payment flow between buyers and sellers of other tokens on their exchange. Other variables are covered under the Data section.

3. Data

Table 1: Descriptive statistics for sample of 86 blockchain tokens (N=monthly)

	N	mean	sd	min	p25	p50	p75	max
Token price at close, USD	979	1.73	6.4	0.0	0.0	0.2	0.9	104.6
Average token mkt cap, mth USD mil	979	701.84	12638.3	0.0	2.9	20.8	113.9	390000
BTC price at close, USD	979	6788.17	3766.3	223.1	4403.1	6835.8	9114.7	19065.7
Average Bitcoin price, mth USD	979	6944.99	3865.4	228.0	4096.0	7772.0	9003.0	15312.0
ETH price at close, USD	947	490.32	290.4	0.7	289.4	452.0	670.8	1278.7
Average Ether price, mth USD	951	498.66	282.2	1.0	305.0	519.0	629.0	1137.0
Diff in log Token price at close	893	-0.07	0.8	-4.1	-0.5	-0.1	0.3	7.0
Diff in log Bitcoin price at close	893	0.03	0.3	-0.6	-0.2	0.1	0.3	0.6
Diff in log Ether price at close	861	0.06	0.4	-0.8	-0.2	-0.0	0.5	1.3
Signif deployment milestone dummy	979	0.41	0.5	0.0	0.0	0.0	1.0	1.0
Percent tokens allocated to insiders	979	25.36	22.4	0.0	10.0	20.0	33.0	92.0
Percent tokens allocated to mining	979	17.37	28.7	0.0	0.0	0.0	28.0	99.0

The primary source of our data is the Cryptocompare.com API, which is used by over 500 companies across the blockchain space, and media platforms such as Yahoo Finance.[3] On 18 July 2018, we downloaded data on 86 blockchain tokens, or ICOs. This data includes the daily closing token price in Bitcoin, the daily closing US dollar exchange rate of Bitcoin / Ethereum / Litecoin and Ethereum Classic, data on cryptocurrencies raised by each ICO, estimated total US dollars raised, and total supply of each token. Where appropriate we convert a token price denominated in Bitcoin into a US dollar price. For our robustness check, we form monthly averages (mean value for the month) from daily time series. Observe how the peak value of BTC declines from USD 19,065 to USD 15,312 when moving from closing prices to monthly average. It is notable that more token prices ("cross rates") are available in Bitcoin than in US dollars. We calculate token market capitalizations by multiplying token price by the total supply of tokens. These values are charted in Figure 1. Market capitalization is the least worst way to visualize the importance of each token, but is prone to many issues including inconsistent ability to exchange, locked tokens and tokens that are no longer accessible. The data on invested capital is declared by the issuer and can come in two forms: (1) a disclosed quantity of cryptocurrencies, or (2) a US dollar equivalent. Using the last closing cryptocurrency price prior to the official end of the ICO period, we estimate the parallel figure when one is absent. This may assume a token raised funds in Bitcoin because it was launched prior to the launch of Ethereum. This may assume a token raised funds in

[3] https://min-api.cryptocompare.com/

Ether because it began life as an ERC-20 token that operated on the Ethereum platform. The data is unbalanced and covers the period between 2 December 2014 to 17 July 2018, part of which is summarized in Table 1.

We use the frameworks defined in section 2 in order to classify our tokens. The four key functional designations of the token framework are: (1) payment, (2) utility, (3) asset and (4) yield. We note that 4 functionalities enable $2^4 = 16$ potential functional combinations, and that not all combinations are present in the sample. Each included token has at least one of these functionalities. All the functional token specifications are identified through the dummy variables in Table 2. The number of tokens with payment functionality is 43 + 8 = 51, and the number with utility functionality is 43 + 26 = 69. When all the dummies are equal to zero, this is the reference state which corresponds to a hybrid payment and utility token - the most common token type in the sample. Delineating this reference category, and explicitly excluding it from all regressions, is necessary to prevent multicollinearity. There are 11 tokens linked to off chain assets and 14 tokens promising a dividend like yield.

Table 2: Token dummy statistics

	Description	Number	Share
Counter	Total number of tokens	86	1.00
Counter	Hybrid payment / utility functionality	43	0.50
TPAY	Payment functionality (No utility)	8	0.09
TUTE	Utility functionality (No payment)	26	0.30
TASSET	Asset functionality	11	0.13
TYIELD	Yield functionality	14	0.16
TSTAKE	Stake rewards	8	0.09
TSOLE	Sole medium of exchange	35	0.41
TDEAD	No longer trading	9	0.10

Hybrid, payment and utility are mutually exclusive token designations, however other dummy types are not mutually exclusive. 10% of tokens have neither payment nor utility functions.

In particular, TPAY is equal to 1 when the token has a payment functionality but no utility functionality. TUTE is 1 when the token has utility functionality but no payment functionality. TASSET is 1 when the token is linked to an off-chain asset. TYIELD is 1 when the token promises to pay a dividend in a token other than itself. The functional dummies (plus reference category) are considered together as a set of groups that span the sample. The other dummies are Boolean in nature, and reflect a default state where they do not apply. If TSTAKE is 1, then the issuer envisions its token within a proof of stake style platform that pays out a reward in itself. The reference category when TSTAKE is 0 is that the token is expected to indefinitely exist on a blockchain without stake rewards (e.g. proof of work). If the white paper, or the platform website, of a token claims that its token will be the sole medium of exchange, or the sole means of payment of the platform fee, then the TSOLE dummy is equal to 1. The reference state where TSOLE equals 0 is that either the platform contains alternative media of exchange, or that it does not possess a utility functionality. Calculating interaction terms, such as TASSET * TYIELD (which would estimate the additional mean difference between this type of hybrid token relative to a hybrid payment and utility token), is not appropriate as these would be small sub-samples of four or less tokens.

Many tokens are issued prior to the implementation of their product. In order to control for this, we include a deployment dummy. If a significant element of its product road map is deployed, then from that month, its TDEPLOY dummy is coded as 1. If this is coded 0 then the project has no significant products ready for use. Additionally, we track trading activity at the time of data download. If a token has not traded on an exchange within the week prior to the data download, then the TDEAD dummy is coded as 1. If this dummy is coded 0, then the token continued to trade on an exchange that provides data to Cryptocompare at the time of data download.

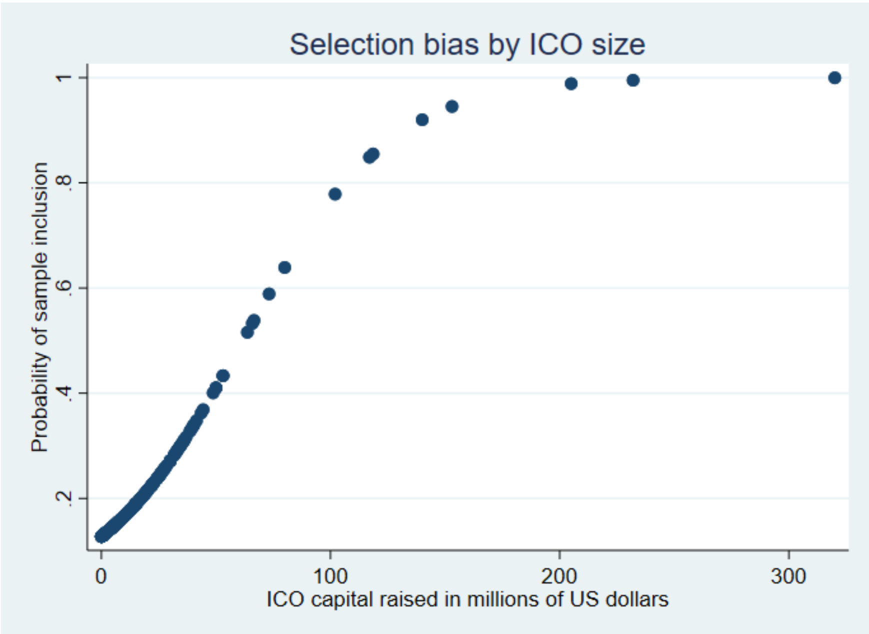

Figure 4: Blockchain token selection bias

The variable RINSIDER is the proposed proportion of tokens reserved for founders, employees, company vehicles, trusts and advisors. This is distinct from tokens that are sold during the token generation event and the raised funds specified for payment or transfer to insiders (cash out). This category does not include early investors. RINSIDER can be thought of as retained interest in the future success of a project. RINSIDER does not adjust for ex post changes in how tokens are distributed e.g. when tokens reserved for insiders are later airdropped to users. RMINE is the proposed proportion of tokens that will either be released in the future for mining (e.g. transaction processing services similar to Bitcoin), or for future partnerships and marketing. When less tokens are sold to investors than intended, these proportions end up higher, irrespective of whether such tokens are then held by the issuer e.g Ripple, or are burnt (permanently eliminated). Both of these variables are ratio scaled.

In figure 4, we chart the selection bias of our sample of 86 blockchain tokens, by plotting probability of inclusion versus US dollars raised at ICO. At the time of download, 2700 coins and tokens were identified on the Cryptocompare platform. 465 (17%) of these were designated as ICOs i.e. that they had raised capital from third parties. Our sample of 86 tokens are 18% of this group. The probability of sampling is correlated to ICO size in dollars. This is primarily driven by the data relationship between Cryptocompare and the trading exchange providing the underlying time series. A token must be listed on an exchange, and a formal agreement exist between Cryptocompare and an exchange, that enables this data to be provided via Cryptocompare's API. A plausible justification of the size bias to this relationship is that the listing of cryptotokens on exchanges is often facilitated by monetary payments from a token team to an exchange.[4] Unfortunately, it is not possible to utilize a Heckman correction to adjust our empirical results for these selection biases, as we cannot identify all the missing time series observations such a procedure requires.

4. Methodology

To test our four hypotheses we perform an ordinary least squares regression. An advantage to this approach arises from the data being formed in unbalanced panels - which are outside the scope of some alternative methods. Feasible GLS modeling for example, which allows direct specification of auto-correlation and heteroskedasticity across panels, is ruled out as modeling for auto-correlated errors requires equally spaced data, while modeling for cross-sectional errors requires balanced panels. We begin by examining the non-stationarity of our data by carrying out Augmented Dickey Fuller (ADF) tests on the price of Bitcoin and Ether, using Akaike Information criteria (AIC) to choose the number of lags, and do not reject the null of a unit root. ADF tests on the first difference of the log of monthly closing Bitcoin and Ether prices do reject the null. These results suggest that Bitcoin and Ether are integrated of order 1 and justify the use of first difference of logs to ensure stationarity.

The sample time series are less straightforward. We use Fisher-type tests for panel unit roots (Choi, 2001), that apply ADF tests to each panel. These are four statistical tests under the null hypothesis that all panels contain a unit root, versus the alternative hypothesis that at least one panel has a unit root. For one and two lags, the Fisher-type tests reject the null that all panels include a unit root. This implies that some (or all) of the panels are stationary. We note that significant price declines such as that seen in 2018, consistent with the bursting of a financial bubble (Brunnermeier and Oehmke, 2012), may cause pseudo-stationarity. The Fisher-type tests do not reject the null under 3 lags, but may be over specified. When testing monthly average market capitalization (rather than monthly closing price), the Fisher type tests do not reject the null under 2 lags, but reject the null when the first differences are taken. Overall we choose to use first differences of logs to ensure symmetric distributions of the price variables. The correlation coefficient matrix for before and after these transformations are shown at the end in Table 7 and 8. Serial correlation within panels is addressed with cluster robust standard errors (discussed below).

[4] http://uk.businessinsider.com/cryptocurrency-exchanges-listing-tokens-cost-fees-ico-2018-3

Therefore we formulate a linear model, for our panel ordinary least squares regression tests, using the first difference of price at monthly close. The daily token closing price observations in Bitcoin are converted into US dollars, and we select the last observation for each month. This forms the basis for the key dependent variable of our model DLPX, the first difference of the log of monthly closing ICO token prices, in US dollars, for 86 separate blockchain tokens. Independent variables include DLBTC, the first difference of the log of monthly closing price of Bitcoin, and DLETH the first difference of the log of monthly closing price of Ether. A summary of our linear empirical model is given in equation 1.

$$\Delta(ln\mathbf{y}_t) = \alpha + \beta\Delta(ln\mathbf{x}_t) + \gamma\mathbf{z} + \epsilon_t \tag{1}$$

Where:

$\Delta(ln\mathbf{y}_t)$ = first difference of the log of monthly closing ICO token prices in US dollars at time t.

$\Delta(ln\mathbf{x}_t) = k \times 1$ vector of the first difference of log of monthly closing benchmark crypto prices at time t.

$\mathbf{z} = p \times 1$ vector of token dummies and token distribution ratios.

ϵ = error term with mean zero and unit variance.

α = constant.

$\beta = k \times 1$ coefficient vector.

$\gamma = p \times 1$ coefficient vector.

We conduct multiple regressions to test the significance of the set of Bitcoin and Ether price variables, token function, feature, and distribution dummies. For clarity, our panel OLS methodology stacks each change in price for each of the 86 blockchain tokens, regresses them on the related independent variable observations, and estimates a single coefficient and standard error for each independent variable across the entire sample. It is sometimes referred to as a pooled OLS model. The intercept (results not shown) ensures that the mean of the error term is zero. This can be written in matrix notation (equation 2), where the first difference in logs is folded into the variables where appropriate, and subscript *it* reflects the value of the variable for blockchain token *i* at time *t*.

$$\mathbf{y}_{it} = \alpha + \boldsymbol{\beta}^T\mathbf{x}_{it} + \boldsymbol{\gamma}^T\mathbf{z}_i + \epsilon_{it} \tag{2}$$

Given that we are formulating and testing a linear regression model, standard OLS assumptions apply with respect to linearity, spherical error terms, and exogeneity. It is not possible to run a fixed effects panel model with token dummies given the fact that many of the dummies are non-varying within our ICO token panels i.e. any such dummy effect would be incorporated in the panel fixed effect. We use cluster robust standard errors (Cameron and Miller, 2015) as it is likely that regression model errors are correlated within clusters (visible when graphing residuals - not shown). Cluster robust adjustments requires the additional assumption that the number of clusters goes to infinity. Moulton (1986) notes how the effect of within cluster correlation can be particularly pronounced when analyzing a policy variable, or aggregated regressor, that takes the same value for all observations within a cluster - which applies to almost all our token dummies. Cluster-robust standard errors also helps address the heteroskedasticity identified in the data. For a final robustness check we also calculate the implied market capitalization by multiplying daily token prices by total token supply - and rerun the analysis with this data.

5. Results and Discussion

Table 3: Determinants of token price change

	[A]	[B]	[C]
DLBTC	0.221	0.222	0.222
DLETH	0.733***	0.733***	0.732***
TPAY	-0.106*	-0.104*	-0.108*
TUTE	-0.017	-0.020	-0.019
TASSET	-0.017	-0.019	-0.020
TYIELD	-0.065	-0.066	-0.068
TSTAKE	-0.006		
TDEPLOY	-0.053	-0.051	-0.053
TSOLE	0.012	0.014	
RINSIDER	-0.000	-0.000	
RMINE	0.000		
aic	1791.917	1787.959	1784.120
bic	1849.015	1835.540	1822.184
Adjusted R^2	0.223	0.224	0.226
n tokens	86	86	86
N observations	861	861	861

All models refer to POLS using cluster-robust standard errors.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

As discussed above, the dependent variable DLPX is the first difference of log token price at close, which given a monthly data set approximates the monthly percentage change in price. Column [A] of Table 3 is a general specification containing all the explanatory variables. The reference state when all the dummies take the value 0 is that the token is a hybrid payment and utility token with no asset or yield function. In Table 3 column [B] and [C] we reduce the number of independent variables. Column [B] is focused on two aspects raised by the prior literature (and the testable hypotheses), sole media of exchange and tokens reserved for insiders. Note that none of the core functionality dummies can be removed without impacting the meaning of the reference state. All three specifications find 99.9%

statistical significance on the first difference in log price of Ether. As the dependent variable and the independent price variables are logs, the coefficients β_k are elasticities (where k is the related independent variable). Therefore our results indicate that a 100% change in the price of Ether leads to a 73% change in the price of our sample of blockchain tokens. The coefficient on the first difference in log price of Bitcoin is not statistically significant. Together these findings reject the null of no relationship in favor of Hypothesis H1, that Ether is a driver of the price of other tokens. In terms of our token function dummies, the majority are negative and not significant, with two exceptions. The payment dummy TPAY is negative and statistically significant at the 95% level. This result rejects the null of no relationship in favor of Hypothesis H2, that token function is impactful. Within our sample, payment protocols without associated utilities are predicted to have more negative percentage changes in value. The TSOLE dummy has a positive coefficient, however this result is not statistically significant at the 95% level. Adding in the lack of evidence of statistical significance on TSTAKE, these results do not reject the null of no relationship between these token features and token price, with respect to Hypothesis H3. In terms of Hypothesis H4, we are unable to reject the null that tokens distributed to insiders or future service providers do not impact token price. Column [C] is designated the empirical model based on the Akaike (AIC) and Bayesian Schwarz Information Criteria (BIC). The lower the AIC and BIC, the more appropriately specified the model.

Table 4: Differences arising from fund raising

	[C]	[D]	[E]
DLBTC	0.222	-0.089	0.478***
DLETH	0.732***	0.996***	0.511***
TPAY	-0.108*	-0.101*	-0.071
TUTE	-0.019	-0.031	0.023
TASSET	-0.020	-0.066	-0.054
TYIELD	-0.068	-0.091	0.014
TDEPLOY	-0.053	-0.052	-0.088
aic	1784.120	1237.312	621.377
bic	1822.184	1271.358	653.349
Adjusted R^2	0.226	0.205	0.281
n tokens	86	66	26
N observations	861	521	402

All models refer to POLS using cluster-robust standard errors.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 4 we explore the influence of ICO funding type. Column [C] is identical between Table 3 and 4. In column [D] we form a sub-sample of tokens that disclosed raising Ether at the time of ICO, or are ERC-20 tokens.

In column [E] we include tokens that raised Bitcoin at time of ICO. All of this latter set of tokens will have either disclosed the Bitcoin raised or launched prior to the launch of Ethereum. These two groups are not mutually exclusive as some will have raised funds in both Bitcoin and Ether. Column [D] of Ether fund raisers see an increased correlation with Ether. A 100% change in the price of Ether leads to a 99.6% change in the price of the blockchain token, and the TPAY dummy remains negative and statistically significant. The TPAY dummy in column [D] relates to 5 payment functionality only tokens. The coefficient on Bitcoin price changes becomes negative. Column [E] of Bitcoin fund raisers see a decline in correlation with Ether, but the Bitcoin price coefficient becomes statistically significant. This model suggests that a 100% change in the price of Bitcoin and Ether leads to a 48% and 51% change in the price of the sub-sample of blockchain tokens respectively. The TPAY dummy loses statistical significance. This result suggests that the form of fund raising, or underlying platform, is important to the performance of a token, and that it is Payment tokens raising Ether that have statistically significant changes in price. We advise caution regarding the interpretation of the token dummies under the Bitcoin funded sub-sample [E] due to the decreased sample size of 26 tokens.

Table 5: Robustness check - Bitcoin variable and no longer trading

	[C]	[Y]	[Z]
DLBTC	0.222		0.222
DLETH	0.732***	0.826***	0.732***
TPAY	-0.108*	-0.107*	-0.108*
TUTE	-0.019	-0.019	-0.020
TASSET	-0.020	-0.018	-0.024
TYIELD	-0.068	-0.068	-0.070
TDEPLOY	-0.053	-0.054	-0.051
TDEAD			0.010
aic	1784.120	1787.267	1786.102
bic	1822.184	1820.574	1828.924
Adjusted R^2	0.226	0.222	0.225
N observations	861	861	861

All models refer to POLS using cluster-robust standard errors.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

In Table 5 we perform two robustness tests on the empirical model. Column [C] is identical between Table 3 and 5. In column [Y] we drop the not statistically significant Bitcoin price variable. In column [Z] we control for the tokens that have not traded recently using the TDEAD dummy. We note that both models have hardly any impact on our results, but do lead to an undesirable increase in the AIC and BIC ratios.

In Table 6 we review robustness by rerunning the modeling from Table 3 with token market capitalization and

Table 6: Robustness check using first difference of log market capitalization (DLMMC) as the dependent variable, and monthly average prices

	[A2]	[B2]	[C2]
DLMBTC	0.126	0.127	0.128
DLMETH	0.949***	0.949***	0.947***
TPAY	-0.090*	-0.085*	-0.090*
TUTE	-0.025	-0.029	-0.027
TASSET	-0.030	-0.031	-0.032
TYIELD	-0.060	-0.059	-0.061
TSTAKE	-0.032		
TDEPLOY	-0.034	-0.029	-0.031
TSOLE	0.016	0.018	
RINSIDER	-0.000	-0.000	
RMINE	0.000		
aic	2249.128	2245.240	2241.396
bic	2306.281	2292.868	2279.498
Adjusted R^2	0.130	0.132	0.134
n tokens	86	86	86
N observations	865	865	865

All models refer to POLS using cluster-robust standard errors.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

monthly averages of our price data. The dependent variable becomes the first difference of log monthly average market cap (DLMMC) for each of our tokens. This moderates the impact of outliers and checks if token supply impact our results. The correlation coefficient matrix for before and after these transformations are shown at the end in Table 8. The Bitcoin variable is DLMBTC first difference in log monthly average of the Bitcoin price, and the Ether variable is DLMETH first difference in log monthly average of the Ether price. All the other variables are unchanged. We observe that the statistical significance on the Ether and TPAY dummy coefficients remain. The adjusted R^2 is lower and that the AIC and BIC criteria are higher when compared to Table 3.

Given the results of our analysis, we can now examine our hypothesis in order.

- H1: ”Price changes in Bitcoin and Ether cause price changes in ICO tokens.”

We find strong evidence of a positive relationship between the price of Ether and price of the blockchain tokens contained in our sample, at the 99.9% statistical significance level. We find weaker evidence that the price of Bitcoin impacts these tokens. For the full dataset in Table 3 there is no finding of statistical significance on the Bitcoin price coefficient. However for the subset of tokens that raise funds in Bitcoin, Table 5 puts forward evidence that Bitcoin does have a positive relationship at the 99.9% statistical significance level. Our results are consistent with Ciaian et al. (2017), which performed a ADRL analysis on Bitcoin and a sample of altcoins, and detected a selection of cointegration relationships particularly over shorter time periods. Specifically, Ciaian et al. (2017) find a negative relationship between Bitcoin and an index of altcoins, which they ascribe to competition effects across a given menu of investment options. We note that a Vector Auto Regressive or Vector Error Correction Model would provide more information on the direction of causality, but for our dataset would be over specified. Our work provides additional evidence that ICO tokens, which represent an underlying business or platform, are a separate asset class from Bitcoin.

- H2: ”Token function impacts the relationship between an underlying business value and its market price..”

We confirm a negative and statistically significant coefficient at the 95% level, on our payment only token function dummy, under multiple different specifications. The utility only dummy has a negative coefficient, but no statistical significance. Our results suggest that either industry specific frictions may not justify a new method of payment, or that payment and utility may be an optimal combination in terms of driving value. We argue that it is rational to discount the idea that these payment only tokens are competing with Bitcoin (and losing), as the tokens in the sample are proposed businesses, not merely potential stores of value. The yield dummy, which some might argue would add value to a token consistent with a dividend discount stock valuation model (Gordon, 1959), did not lead to any statistically significant result, and had a negative coefficient.

- H3: ”Token's promising the characteristics of stake rewards and sole medium of exchange on a platform, trade at a higher price.”

The stake reward dummy was not statistically significant. For the purposes of discussion, we juxtapose this feature with the function of yield, because yield and staking token characteristics promise either: (1) a monetary dividend in another currency e.g. Ether; or (2) a scrip-like dividend in the same token (more shares of the token's aggregate value). There are three plausible reasons for their lack of statistical significance. The first is that token value may accrete from these features from the date they are implemented, and for the majority of our sample, they have not been instituted yet. Another point is that these features or rights can exist at two levels: those that are made in associated documentation, and those that are written in the software code (Cohney et al., 2019), and these reward promises are still marketing promises rather than hard coded. A final reason might be that it is in fact very difficult to pay such rewards. Large quantities of tokens are held in aggregated wallets at exchanges where they are bought or sold. This creates problems with the identification of ownership and payment of any rewards.

Although we find a positive coefficient on the TSOLE dummy, suggesting that definition as the sole medium of exchange is a value increasing utility token feature, we are unable to find sufficient statistical evidence to reject a null hypothesis that being the sole medium of exchange has no impact on blockchain token prices. Therefore we fail to present empirical evidence in line with the work of Catalini and Gans (2018).

- H4: ”ICOs with a higher proportion of outstanding tokens reserved for the token issuer, and a lower proportion of tokens reserved for mining, trade at a higher price.”

Our study is unable to reject the null hypothesis that tokens reserved for insiders and tokens earmarked for mining have no impact on blockchain token price. We note that in theory payments for mining and future partnerships should be made at the expected value of services rendered. The effect of insider ownership on the other hand reflects two alternative perspectives: (1) that a high stake reflects skin in the game and inside information about the quality of the business (Chod and Lyandres, 2018), and (2) that the investor’s share of platform economics is being circumscribed. These factors may become more tractable to economic analysis once an increasing proportion of these platforms are deployed and achieve scale.

6. Conclusion

One way to introduce the phenomena of cryptoassets and blockchain is to say that they have raised great expectations among technologists and financial professionals. This salience is highlighted by the sizable market cap of Bitcoin, a digital token that is the leading medium of exchange for a plethora of imitators and extensions. Given the prices of two major cryptocurrencies and a set of dummies related to token function, token features and token distributions, we tested four hypotheses in order to explore the broad topic of token value and price. We show that the designed functional connection can be effective, thus linking a project that has a value, with a blockchain token that has a price. This is in the absence of a legal connection or claim.

This paper is a step towards illuminating the question “What can a blockchain token embody and connect?” The public blockchains on which the sampled tokens operate, are systems where no higher authority is necessary to create trust between distrusting agents. This decentralization equates to no single point of control, and a reduction in establishment costs. Without system critical gatekeepers, such as governments or banks, blockchain is dramatically reducing the barriers to create provably scarce tradeable tokens. These tokens are being used to raise crowdfunding and digitize real world assets. From here it is only a short step to trustlessly digitizing rights and responsibilities.

Our results complements regulatory actions such as SEC (2018), which posits that tokens may be an investment contract in a common venture. It supports both FINMA (2018) and FCA (2019) in distinguishing tokens by function. Additionally these findings respond to the prima facie argument that blockchain is not significant. To date, cryptoassets are “a minority sport with few users”, while blockchain has seen limited wider application and adoption (Roubini, 2018). However, the logic of slow adoption becomes clear once we accept that blockchain is not a revolution in higher performance services (Croman et al., 2016). Capacity constraints is a feature of blockchain’s decentralization functionality (Lo and Medda, 2018). This lower relative capacity handicaps blockchain’s ability to displace centralized financial systems, at the same time as its decentralization feature enables new types of competitors, new economic structures, and new methods of value discovery.

We argue going forward that the opportunity in blockchain may be in creating novel digital tokens for abstract assets and liabilities that have never traded before, rather than tokenizing existing assets such as equity shares. Future research directions may include how tokens could be used to delineate responsibilities digitally, or solve problems of externalities by expressing currently unobserved social costs as digital blockchain tokens. Such research would provide evidence that blockchain can change the economic behavior of agents, as opposed to changing the distribution of economics and control.

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Table 7: Correlation coefficient matrix - primary model

	(1)					
	TOKENUSD	BTCUSD	ETHUSD	DLPX	DLBTC	DLETH
TOKENUSD	1					
BTCUSD	0.105**	1				
ETHUSD	0.116***	0.839***	1			
DLPX				1		
DLBTC				0.347***	1	
DLETH				0.474***	0.621***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Correlation coefficient matrix - secondary model

	(1)					
	MKTCAP	BMTH	EMTH	DLMMC	DLMBTC	DLMETH
MKTCAP	1					
BMTH	0.0595	1				
EMTH	0.0804*	0.862***	1			
DLMMC				1		
DLMBTC				0.232***	1	
DLMETH				0.372***	0.563***	1

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$