UCL

UCL Centre for Blockchain Technologies

Discussion Paper Series

Q4 2020

CBT

Foreword

It is, as usual, my great pleasure to present the selection of papers for the last quarter of 2020. Here, we are reporting three interesting papers concerning market concentration, network effects, and bookkeeping in the cryptocurrency world. This selection of papers aims to help the authors to increase their impact on both academia and industry and provides CBT associates a glimpse of some of the research activities in our vast and productive community.

Enjoy your reading!

Tomaso Aste
UCL CBT Scientific Director & Chairman of the Editorial Board

April 2021

Acknowledgement
The editorial board wishes to thank Juan Ignacio Ibañez for his high-quality work and strong perseverance, without which this discussion paper series would have never been possible.

Discussion Paper Series Contents

The following are published in this edition:

Editorial Board

Discussion Paper #1

Cryptoasset Competition and Market Concentration in the Presence of Network Effects

Konstantinos Stylianou, University of Leeds

Leonhard Spiegelberg, Brown University

Maurice Herlihy, Brown University

Nic Carter, Coin Metrics

Abstract

When network products and services become more valuable as their userbase grows (network effects), this tendency can become a major determinant of how they compete with each other in the market and how the market is structured. Network effects are traditionally linked to high market concentration, early-mover advantages, and entry barriers, and in the cryptoasset market they have been used as a valuation tool too. The recent resurgence of Bitcoin has been partly attributed to network effects too. We study the existence of network effects in six cryptoassets from their inception to obtain a high-level overview of the application of network effects in the cryptoasset market. We show that contrary to the usual implications of network effects, they do not serve to concentrate the cryptoasset market, nor do they accord any one cryptoasset a definitive competitive advantage, nor are they consistent enough to be reliable valuation tools. Therefore, while network effects do occur in cryptoasset networks, they are not (yet) a defining feature of the cryptoasset market as a whole.

Keywords: Network Effects, Metcalfe, Metcalfe's Law, Concentration, Monopolization, Monopoly.

Cryptoasset Competition and Market Concentration in the Presence of Network Effects

Konstantinos Stylianou
University of Leeds
Leeds, United Kingdom
k.stylianou@leeds.ac.uk

Leonhard Spiegelberg
Brown University
Providence, Rhode Island, USA
lspiegel@cs.brown.edu

Maurice Herlihy
Brown University
Providence, Rhode Island, USA
herlihy@cs.brown.edu

Nic Carter
Coin Metrics
Boston, Massachusetts, USA
nic@coinmetrics.io

ABSTRACT

When network products and services become more valuable as their userbase grows (network effects), this tendency can become a major determinant of how they compete with each other in the market and how the market is structured. Network effects are traditionally linked to high market concentration, early-mover advantages, and entry barriers, and in the cryptoasset market they have been used as a valuation tool too. The recent resurgence of Bitcoin has been partly attributed to network effects too. We study the existence of network effects in six cryptoassets from their inception to obtain a high-level overview of the application of network effects in the cryptoasset market. We show that contrary to the usual implications of network effects, they do not serve to concentrate the cryptoasset market, nor do they accord any one cryptoasset a definitive competitive advantage, nor are they consistent enough to be reliable valuation tools. Therefore, while network effects do occur in cryptoasset networks, they are not (yet) a defining feature of the cryptoasset market as a whole.

KEYWORDS

network effects, Metcalfe, Metcalfe's Law, concentration, monopolization, monopoly

ACM Reference Format:

Konstantinos Stylianou, Leonhard Spiegelberg, Maurice Herlihy, and Nic Carter. 2020. Cryptoasset Competition and Market Concentration in the Presence of Network Effects. In . ACM, New York, NY, USA, 13 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn

1 INTRODUCTION

The rapid appreciation and popularization of cryptoassets over the past few years has incited a large body of scholarship on understanding their behavior and their positioning in the market, particularly financial markets. As cryptoassets gradually became a household investment and transaction medium, they began to invite greater regulatory and investor scrutiny, which created the need to better understand their function as a market of their own and as market that forms part of the greater economy. While early analyses focused on simple economic illustrations of the functioning of cryptoasset networks in isolation, later work started exploring market-wide phenomena, including the dominance patterns of some cryptoassets over others.

Since cryptoassets are based on blockchain networks and are therefore network markets, one important parameter that reflects and determines their behaviour is the relationship between their userbase and their value. This relationship has a long history in network markets under the theory of *network effects*. Network effects theory states that the value of a product or service V is co-determined by its userbase u. Then, for products or services that obey network effects, one can derive the value of the network, and therefore their relative value to each other too, for a given userbase assuming that the relationship between V and u is known, for example $V \propto nlog(u)$, $V \propto u^2$, $V \propto 2^u$ etc.

Initially, this insight attracted attention because of its predictive potential of cryptoasset valuation. Indeed a number of studies attempted to develop valuation models based on network effects that could be used by investors to predict the future value of their assets and the value of the market as a whole. However, the implications of network effects go far beyond valuation and, understood properly, they inform also the structure and competitiveness of the market making them a key input into policy-making and regulatory decisions. Most notably, markets that are characterized by network effects are commonly thought to be *winner-take-all* markets, where first mover advantage is key, entry barriers are high, networks hit tipping points of no return, and contestable monopolies or high concentration can be the natural state of the market. This is for two reasons: firstly, because the value of joining a network is increasing in the number of other network adopters, because the bigger the number of existing adopters the greater the utility every new adopter derives from it (*pure network effects*), and secondly, because for every new adopter joining the network, existing adopters also benefit (*network externalities*). In both cases bigger equals better (everything else equal), creating an incentive for users to join the network where the value will grow larger both for new and for existing users, which creates a snowball effect. This kind of power concentration in networks that exhibit network effects usually makes regulators uneasy, and therefore, if cryptoassets exhibit

https://doi.org/10.1145/nnnnnnn.nnnnnnn

network effects, they would (and should) attract higher regulatory and investor scrutiny.

Extant literature on network effects in cryptoassets is limited and has focused almost exclusively on confirming or rejecting, usually for Bitcoin only, a specific application of network effects, namely Metcalfe's law, which states that the value of a network is proportional to the square of its users ($V \propto u^2$), and, if confirmed, it would be a useful valuation tool. However, this line of literature presents only a binary distinction between the existence or not of a specific type of network effects, focuses only on valuation, uses sub-optimal data, and has also been temporally limited to the period before the recent resurgence in mid 2019, or excludes periods, therefore missing key parts in the cryptoasset market evolution.

By contrast, our analysis takes a more comprehensive view of network effects in cryptoassets, and, while it confirms that network effects occur in cryptoassets, it shows that they do not have the usual implications associated with them in terms of according competitive advantages, resulting in market concentration, or serving as a reliable valuation tool. Firstly, we define network effects to occur when the value of a cryptoasset network changes supra- or infra-proportionately to changes in its userbase, thereby showing both positive and reverse network effects, while not being constrained by a specific version of network effects. We also use two proxies for value and userbase each to better capture what users perceive as the value of the network and how the network size (userbase) should be measured, and we base our results on cleaner vetted data. Moreover, we examine multiple cryptoassets to get a broader view of the industry, as opposed to previous works which focused on Bitcoin. Lastly, our analysis covers the entire history of the studied cryptoassets, which includes the valuation spikes and subsequent declines in 2014, 2017 and 2019. The spike in 2019 and the preceding decline from the heights of 2017 are particularly valuable because they help us show that the results obtained in previous studies which sampled only up to early 2018 do not hold based on more recent history.

2 BACKGROUND, MOTIVATION AND IMPLICATIONS

Network effects were first studied in the 1970s to more accurately capture the value and growth of telecommunications networks [28]. The intuition was that when the nature of a product or service is such that it relies on linking users together, the value of the product V is co-determined by its userbase u. More specifically, for every user added to the userbase of a product, value is created not just for the joining user but for existing users as well. As a result, each new user derives value from joining a network that is relative to the size of the network (pure network effects) and creates an externality in the form of value that is captured by the network of existing users (network externality). Conversely, for every exiting user, value is lost both for the exiting user and for existing users. This type of network effects was called direct network effects to distinguish it from later extensions to the theory, which accounted for the effects changes in the network's userbase have on complementary products and services developed for that network [8]. This latter type was called indirect network effects, and it is not the kind that will concern us here.

The powerful implication of (direct) network effects is the increasing returns to the userbase and ultimately to the product exhibiting network effects. Because for products that exhibit network effects every new adopter makes the product more valuable relative to existing size of its network, it creates incentives for other adopters to adopt the product with the bigger network over its competitors. Consequently, the more the userbase grows the more it invites further growth rendering the product increasingly more valuable and competitive. The exact relationship between value and userbase can vary; While one can say that in the most basic version of network effects the value of a product grows linearly with the number of users added to its userbase ($V \propto u$) [32], most commonly network effects are used to describe relationships that are logarithmic ($V \propto nlog(u)$) [5], quadratic ($V \propto u^2$) [23] or other (e.g. $V \propto 2^u$).

Network effects have found application in numerous industries and business models ranging from telecommunications [4, 16], to web servers, PC software [17], airline reservation systems, ATMs [14], and platform systems [7]. Indeed, the intuition and implications of network effects have been so pervasive that they have been invoked in any industry where the consumption or use of a product by consumers makes the product more valuable for others (for a collection of relevant literature see [19]. It is no surprise that cryptoassets have also been hypothesized to exhibit network effects. The combination of the inherent network nature, the meteoric rise in popularity (read: userbase), and the substantial price volatility (read: value) has suggested a strong-if elusive-relationship.

The particular motivation behind the study of network effects in cryptoassets has so far been to discover a valuation formula: if we know the function between userbase and value, then with informed guesses on the network's growth we can predict future prices [26, 30, 33]. But valuation formulas reduce network effects down to a binary distinction represented by a single function. While useful as prediction tools and high-level descriptors of cryptoasset trends, valuation formulas provide little granularity.

Our motivation and goal is, instead, to provide more high-level view of how network effects influence the cryptoasset market as a whole, and particularly what they say about the potential for concentration in the market and about competitive (dis)advantages of one cryptoasset over others. These are the most impactful implications of network effects, and they are desirable for those networks that can exploit them, but undesirable for their competitors or for regulators who have to deal with concentrated markets. We work with numerous cryptoassets so that we can obtain a market-wide overview (limited by how big and representative our sample is), and we study them from their inception until early 2020 which allows us to capture all historically important phases, including the resurgence in 2019, which extant literature has not had a chance to consider. This type of approach allows us to draw insights about the structure and competitive dynamics of the cryptoasset market. It goes back to the early wave of "*Bitcoin maximalism*", which stood for the idea that the optimal number of currencies as alternatives to the mainstream financial system is one, and altcoins will eventually be rendered obsolete as more and more users gravitate toward the biggest, most stable, most widely accepted cryptocurrency, namely Bitcoin. At the time, Bitcoin maximalism was rejected by Vitalik Buterin, the creator of Ethereum, correctly pointing out that the

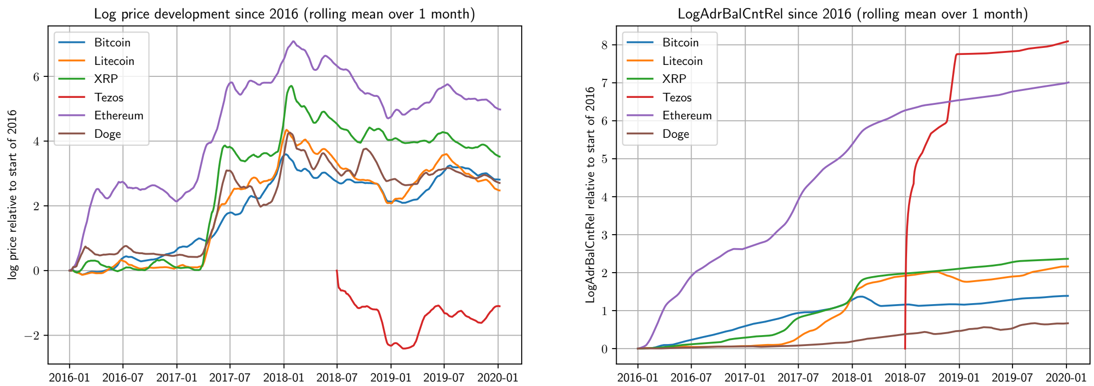


Figure 1: Price and userbase development since 2016.

cryptoasset universe is not a homogeneous thing, and that therefore there is no one single "network" around which network effects would form [6]. We expand on that thinking.

Looking at network effects to study the competitive dynamics of the cryptoasset market and its potential to concentrate around one or a small number of cryptoassets can provide useful insights for industrial policy. Normally, a showing that cryptoassets exhibit network effects would suggest that early cryptoassets have a first-mover advantage and may lock the market in [13, 18, 22], even if they are intrinsically inferior to other comparable cryptoassets [5, 15, 20]. While, the market seems to have moved away from that danger, network effects theory also suggests that, assuming homogeneity, once a cryptoasset hits a tipping point, it may fully prevail because new users will always prefer the cryptoasset with the larger userbase (the so called "winner-take-all" markets, which Bitcoin maximalism relied on) [13, 22]. Homogeneity is, of course, a matter of degree, and it is still likely that, if a cryptoasset exhibits stronger network effects than its peers, it can prevail at least within a sub-segment of the market. The flip side of network effects can also be observed, whereby the loss of a user results in a supra-proportionate loss of value (i.e. more value than the user intrinsically contributed individually), which incites further losses and so on. This means that rapid depreciation is more likely in cryptoassets characterized by network effects. The rapid appreciation and depreciation cycles coupled with the winner-take-all characteristic can in turn result in cryptoasset markets that are successively dominated by a new winner in every era (successive contestable monopolies). Then, if this is the natural state of the market, artificially forcing more competition may not be optimal.

These insights are well-applicable in financial markets. For instance, the influential "Cruickshank report", an independent report on banking services in the United Kingdom prepared for the UK Treasury, which has in turn influenced regulatory and legal decisions [1, 2], warned about the far reaching implications of network effects: "Network effects also have profound implications for competition, efficiency and innovation in markets where they arise. Establishing critical mass is the first hurdle, as the benefits to customers and businesses of a network arise only gradually with increasing use. It is possible to imagine a world in which electronic cash is widely held and used, for example, but much harder to see how to get there. Once a network is well established, it can be extremely difficult to create a new network in direct competition. ... Where network effects are strong, the number of competing networks is likely to be small and the entry barriers facing new networks will be high" [11]. As the fintech industry is heating up, network effects have also been cited there as a strong factor in entrenching existing market power of financial services (see e.g. the recent proposed acquisition of Plaid by Visa [12]), and such risks have also been highlighted in the cryptoasset market, with models showing that certain conditions can allow cryptoasset markets to become oligopolies and market players entrench their position in the market [3, 10].

3 PRIOR LITERATURE AND CONTRIBUTION

A number of papers have investigated aspects of the application of network effects in cryptoasset networks. The focus has been to determine whether the value of cryptoassets (and mainly Bitcoin) complies with network effects, and in particular on whether it follows Metcalfe's law, which is the most popular iteration of network effects and stipulates that the value of a network grows at a rate proportional to the square of the number of users ($V \propto u^2$).

The early influential analysis by Peterson [26] remains the point of reference. Peterson developed a valuation model for Bitcoin's price based on Metcalfe's law for the period 2009-2017, using wallets as a proxy for users, Bitcoin prices as the proxy for value, and a Gompertz function to account for growth. He found that the price of Bitcoin follows Metcalfe's law with R-square of 85 percent. In a revised version of the original paper that extends through 2019, Peterson re-confirms the application of Metcalfe's law to Bitcoin [27]. However, he excludes significant periods of time on the grounds of price manipulation, during which the value of the Bitcoin network, as measured by the USD price of Bitcoin, lies well outside of Peterson's model predictions. Van Vliet [33] enhanced Peterson's model by incorporating Rogers' diffusion of innovation models to better capture population parameters and growth rates. By doing so, van Vliet raised R-squared to 99 percent. Shanaev et al. [30] acknowledge the utility of Peterson's and van Vliet's analyses but depart from them in that their model does not rely on historical data for the estimation of the coefficient of proportionality, which raises an endogeneity problem. They still use Metcalfe's law but only as only as one of the building blocks of their model. Civitarese [9] rejects the applicability of Metcalfe's law to the value of the Bitcoin network by running a cointegration test between price and an adjusted number of wallets' connections.

Gandal and Halaburda [18] use a completely different approach to examine the existence of network effects in cryptoasset networks. They define network effects as the reinforcement effects the price of a cryptoasset has on the price of another cryptoasset. With Bitcoin as the base cryptoasset, the idea is that, if network effects are in place, as Bitcoin becomes more popular (price increase), more people will believe that it will win the winner-take-all race against other cryptoassets resulting in further demand and higher prices. Therefore, network effects would manifest themselves as an inverse (negative) correlation between the prices of the sampled cryptoassets. For the period May 2013 - July 2014, their results showed signs of network effects after April 2014.

Our analysis complements and differs from prior literature in several ways. Firstly, we do not focus on a specific network effects formula; we rather look at when, to what degree, in which cryptoassets, and for what proxies of value and userbase network effects are observable (defined as supra-proportional change in value relative to userbase) regardless of which particular curve/function they follow. Secondly, we go beyond Bitcoin to examine six cryptoassets that we have selected as representative of different features and characteristics to better be able to observe potential industry-wide trends. This helps us notice whether one cryptoasset has the potential to dominate the market or multiple cryptoassets benefit from the same network effect forces. Thirdly, we use different parameters as proxies for value and userbase to more fully capture the functionality and usage of cryptoassets in the market. Importantly, we do not rely on the total number of users as a proxy for userbase like extant literature, because many of those addresses are dormant or permanently inaccessible and therefore economically irrelevant. Fourthly, we study the full history of cryptoassets from their inception to today which allows us to observe their different phases, including the price collapse in 2018 and the resurgence in mid-2019, which dramatically change the picture of network effects and which have been missed by previous studies. Lastly, we work with data sets that have been meticulously cleaned to filter out spurious or manipulative activity, which improves the accuracy of our results compared to data-sets that are pulled unfiltered from the network. Our analysis confirms the existence of network effects, but also that they do not have the results usually associated with them on the market.

4 METHODOLOGY AND DEVELOPMENT

We study the application of network effects in Bitcoin (BTC), Dogecoin (DOGE), Ethereum (ETH), Litecoin (LTC), XRP and Tezos (XTZ). The selection of these cryptoassets was made on the basis of diversity and feasibility. We aimed to study cryptoassets that exhibited different attributes in terms of age, market capitalization and any special features that make them stand out from other competing cryptoassets in order to build a representative sample of the crypto-economy [21]. We also limited the study to cryptoassets for which we could get reliable, standardized time-series data from the cryptoassets' initial release to the time of the study [24]. The unreliability of the prices reported by exchanges in the early days of the industry led us to consider Bitcoin from July 2010, Litecoin from March 2013, and XRP from August 2014âĂŤthe rest from their beginning. Table 1 summarizes the attributes of each chosen cryptoasset.

	Age	Market cap (2020)	Features
Bitcoin (BTC)	Old (2009)	V. Large ($170B)	Popularity, first cryptocurrency, UTXO based
Dogecoin (DOGE)	Old (2013)	V. Small ($0.3B)	"Joke cryptocurrency", early BTC contender , UTXO based
Ethereum (ETH)	Medium (2015)	Medium ($25B)	Turing complete, programmable, account based
Litecoin (LTC)	Old (2011)	Small ($2.6B)	First major BTC fork, UTXO based
XRP	Old (2012)	Small ($8B)	Consensus, fintech-orientated, account based
Tezos (XTZ)	New (2018)	Small ($1.7B)	Centralized PoS, on chain governance, account based

Table 1: List of studied cryptoassets, chosen to cover different characteristics.

We first define network effects. Network effects occur where the value of the network V grows supra-proportionately to the number of users n that participate in the network. Reverse network effects occur where the value V drops supra-proportionately to the number of users n that leave the network. Unless there is a reason to distinguish between positive and reverse network effects, we collectively refer to them as network effects. Therefore, we define network effects to occur in cryptoassets when a positive value change $\Delta V > 0$ is larger than a positive userbase change $\Delta u > 0$, or when a negative value change $\Delta V < 0$ is smaller than a negative userbase change $\Delta u < 0$. Notice that we do not consider that network effects apply when value and userbase move in different directions, e.g. when the value increases while the userbase decreases, regardless of which increases or decreases more.

Thus, network effects occur if

$$\Delta V > \Delta u \geq 0 \ \vee \Delta V < \Delta u \leq 0$$

In our analysis we define change at time t similar to log returns, i.e.

$$\Delta V := \ln \frac{V_{t+1}}{V_t} \tag{1}$$

$$\Delta u := \ln \frac{u_{t+1}}{u_t} \tag{2}$$

Then, we identify appropriate proxies to represent value V and userbase u. To represent V we use two proxies: (a) token price and (b) transaction value. The two proxies represent different aspects of the value users assign to cryptoassets. In theory, even one proxy applied to one cryptoasset would be enough to demonstrate (or not) network effects (as has, for example, been done in previous literature that relied only on token price), assuming the proxy and cryptoasset are representative. However, because cryptoassets are differentiated resulting in diversified usage patterns, and because the chosen proxies express different ways by which users perceive the value of the network, a multitude of cryptoassets and proxies was used in an effort to better represent the industry.

Token Price (PriceUSD): The first parameter we use is token price, which is the fixed closing price of the asset as of 00:00 UTC the following day (i.e., midnight UTC of the current day) denominated in USD (for a detailed explanation of Coin Metric's methodology on toke price see [24]). Token price expresses value in terms of market forces, namely the point at which supply meets demand. It is the value that users as market participants collectively assign to a given cryptoasset by deciding to buy and sell at that price level. We assume that the studied cryptoassets trade under normal market conditions; any acknowledgement of price manipulation that may have occurred at times has been accounted for in the cleaning of data by Coin Metrics [24].

Transaction Value (TxTfrValAdjUSD): The second proxy of choice is transaction value, which expresses the USD value of the sum of native units transferred between distinct addresses per day removing noise and certain artifacts to better reflect the real economically relevant value circulating in the network. The assumption is that as the network becomes more valuable to users, they will use it more frequently and/or to transfer greater value among them. Therefore, transaction value as a proxy sees cryptoassets as means of transaction. We considered and rejected transaction count as an appropriate proxy, because on some networks a large number of recorded transactions are unrelated to value transfer, but rather to the operation of the network, e.g. consensus formation on Tezos [25]. One could retort that even these non-value-carrying transactions reflect engagement with the network and that therefore are an indication of the value of the network to users. Even so, lumping together value-carrying and operational transactions would taint the comparison across cryptoassets, since on some cryptoassets the majority of transactions are operational (e.g. Tezos, see [25]), while on others value-carrying (e.g. Bitcoin).

Next, to represent u we select the following proxies: (a) addresses with non-zero balance (b) trailing 6-month active addresses and . Different ways to represent userbase more fully captures the relationship between value and userbase. We considered and rejected counting userbase based on total number of addresses (like all previous literature), because of the large number of inactive addresses. Contrary to other industries where network effects have been studied and where inactive users are eventually purged from the network (e.g. mobile phone subscriptions, social networks), so that total user count may still be a good approximation of the economically meaningful userbase, this is not the case with cryptoassets. Instead we opted for two variants of addresses with non-zero balance, as defined below.

Addresses with Non-Zero Balance (AdrBalCnt): This proxy represents the sum count of unique addresses holding any amount of native units as of the end of that day. Only native units are considered (e.g., a 0 ETH balance address with ERC-20 tokens would not be considered). The utility of this proxy lies in that it excludes all non-economically active addresses, the assumption being that addresses with zero balance are dormant (similar to bank accounts with zero balance). This choice responds to criticism that has been raised with regard to extant literature that tended to use all addresses or wallets as a proxy for users. Despite our choice of improved metric, it still remains a fact that there is no one-to-one mapping between addresses and actual users, which is a common problem to any network or service, e.g. the same person may have multiple bank accounts. While there are methods to de-cluster actual users from wallets and addresses, these are not sufficiently precise and are unavailable or inapplicable across cryptoassets [**?**]. We also acknowledge that on networks with lower transaction fees it is easier to generate and/or maintain addresses with balance, and to counter that we could raise the amount of native units the counted addresses should have, but this would introduce a subjectivity question without even fully eradicating the initial problem of spurious addresses.

Trailing 6-Month Active Addresses (6MAdrActCnt): This proxy counts all unique addresses that have been active at least once over the trailing 6-month period from the time of measurement. Repeat activity is not double-counted. Traditionally, most userbase measurements are taken in time frames that range from one month to one year. Given that cryptoassets are of relatively young age, which may suggest that their userbase is expected to interact with them less frequently, and that part of their utility involves simply owning them, which does not generate any activity, we decided that a 6-month time frame sufficiently captures active userbase.

Before we derive network effects, we first calculate the Pearson correlation between value V and users u which is informative in terms of their overall relationship. Next, we obtain relevant measurements of network effects. We rely predominantly on the PriceUSD-AdrBalCnt pair of proxies for value and userbase, but additional measurements are in the Appendix. To see how prevalent network effects are in the studied cryptoassets we calculate the ratio of total days to the days where network effects were observed (separately for positive and reverse) for each cryptoasset. To see how strong network effects are we calculate the ratio of total days to the sum of the network effects observations over the days they occurred for each cryptoasset (separately for positive and reverse). To see how strong network effects are in cryptoassets relative to each other we reduce to a 100 day period. The results are presented in Part 5 and the analysis of the results in Part 6.

Metric abbr	Metric meaning
PriceUSD	Token price
TxTfrValAdjUSD	Transaction value
AdrBalCnt	Addresses with non-zero balance
6MAdrActCnt	Trailing 6-month active addresses
NFX	Network effects

Table 2: Legend of metrics in use.

		User proxies	
Cryptoasset	Value proxy	AdrBalCnt	6MAdrActCnt
BTC	PriceUSD	0.878760	0.800890
BTC	TxTfrValAdjUSD	0.771601	0.734617
DOGE	PriceUSD	0.532856	0.255025
DOGE	TxTfrValAdjUSD	0.258791	0.141790
ETH	PriceUSD	0.256837	0.475199
ETH	TxTfrValAdjUSD	0.048093	0.214427
LTC	PriceUSD	0.646814	0.844012
LTC	TxTfrValAdjUSD	0.258648	0.431706
XRP	PriceUSD	0.551157	0.803027
XRP	TxTfrValAdjUSD	0.189622	0.278429
XTZ	PriceUSD	-0.477943	-0.681394
XTZ	TxTfrValAdjUSD	-0.169407	-0.240346

Table 3: Pearson correlation between value and user proxies

5 RESULTS

We are looking for network effects in the relationship between value V and users u of various cryptoassets as represented by the proxies defined previously. Four pairs (2x2 proxies) are possible:

- `Token Price - Addresses with Non-Zero Balance`: This pair demonstrates network effects expressed as the change of monetary value of a cryptoasset relative to the users that hold any amount of that cryptoasset. By counting only accounts with non-zero balance, we filter out economically dormant users.
- `Token Price - Trailing 6-month Active Addresses`: This pair demonstrates network effects expressed as the change of monetary value of a cryptoasset relative to the users that have been active at least once in the trailing 6-month period on that cryptoasset's network. Counting all active users over a recent time segment (usually 1, 6 or 12 months) is a common measurement of network or platform userbase and less conservative than daily active users.
- `Transaction Value - Addresses with Non-Zero Balance`: This pair demonstrates network effects expressed as the change of transaction value of a cryptoasset relative to the users that hold any amount of that cryptoasset.
- `Transaction Value - Trailing 6-month Active Addresses`: This pair demonstrates network effects expressed as the change of transaction value of a cryptoasset relative to the users that have been active at least once in the trailing 6-month period on that cryptoasset's network.

Before we derive network effects, we calculate, based on the above pairs, the Pearson correlation between value V and users u which tells us whether, as a general matter, cryptoasset value and userbase are moving in the same direction. This already provides an indication of whether cryptoassets become more valuable as their adoption increases.

It is evident that only BTC shows a strong correlation between value and userbase, at least when userbase is measured by our main proxy of total addresses with non-zero balance (AdrBalCnt), with LTC showing the next highest correlation, which is, however, average and only holds when value is measured as value in fiat currency (PriceUSD). Correlations when userbase is measured as addresses that have been active in the trailing 6-month period (6MAdrActCnt) tend to be higher although still not consistently so. Higher correlation using 6MAdrActCnt might be explained on the grounds that user activity picks up during phases of large price movements. Overall, the mediocre and inconsistent correlations between value and userbase provide a first indication that a blanket conclusion that the cryptoasset market is characterized or not by network effects is unwarranted.

Next, we obtain relevant measurements based on the PriceUSD-AdrBalCnt pair of proxies for value and userbase as presented in Table 4 and for additional pairs as per above in the Appendix. As explained in the methodology, we believe these are the most appropriate proxies. Column 5 of Table 4 shows prevalence of network effects for each cryptoasset as calculated by the ratio of total days to the days where network effects were observed (separately for positive and reverse). Column 6 of Table 4 shows relative strength of network effects across cryptoassets. We derive that by calculating for each cryptoasset the ratio of days where network effects occurred to the sum of the network effects observations over those days (separately for positive and reverse) and then reducing to a 100 day period. This allows us to compare how strong network effects are across cryptoassets regardless of how prevalent they are across them.

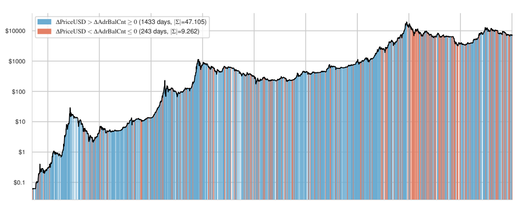
6 ANALYSIS

Our results are useful in reaching a number of conclusions on how network effects inform the structure and evolution of the cryptoasset market.

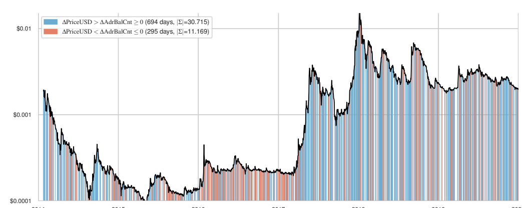
(1) Network effects do not provide precise valuation predictions: The most common application of network effects theory has been to draw insights into future cryptoasset pricing based on the evolution of their userbase. Our results indicate that network effect observations in cryptoassets are frequent but inconsistent and therefore they cannot be relied on, generally, as a valuation tool as previous literature suggests (Figures 2 and 3). They are most frequent in XRP (45 percent of time in the pair Token Price-Addresses with Non-Zero Balance) and least frequent in LTC (29 percent of time in the same pair). While they appear more consistent in ETH and XRP, their results can be somewhat misleading at first glance: ETH's and XRP's userbase (AdrBalCnt) was constantly increasing and so any supra-proportionate increase in price registered as a (positive) network effect observation (blue lines in (c) and (e) in Figure 2). However, the positive network effect observations are frequently

Crypto	Total days	Days of NFX (pos-reverse)	Sum (strength) of NFX (pos-reverse)	Ratio of total days/NFX days (pos-reverse)	Relative strength of NFX (pos-reverse)
Bitcoin	3461	1434	47.1	0.400	3.28
		243	9.2	0.070	3.78
Doge	2175	695	30.7	0.310	4.40
		295	11.1	0.130	3.70
Ethereum	1614	707	33.5	0.430	4.70
		12	0.2	0.007	1.66
Litecoin	2473	722	34.5	0.290	4.77
		354	11.2	0.140	3.16
XRP	1973	901	41	0.450	4.55
		-	-	-	-
Tezos	558	244	10.8	0.430	4.40
		-	-	-	-

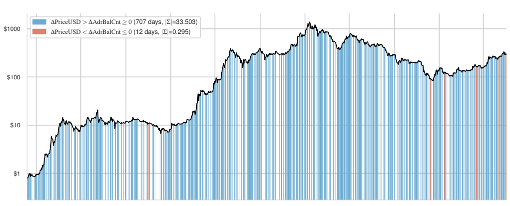
Table 4: Network effects measurements based on the Token price - Addresses with non zero balance proxy pair



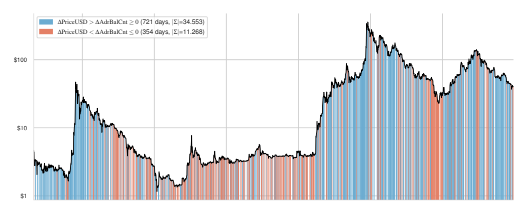
(a) BTC



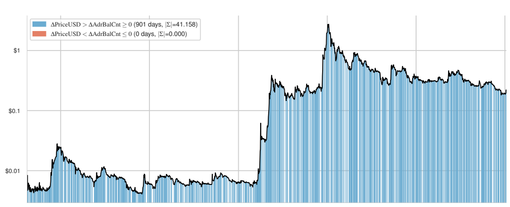
(b) DOGE



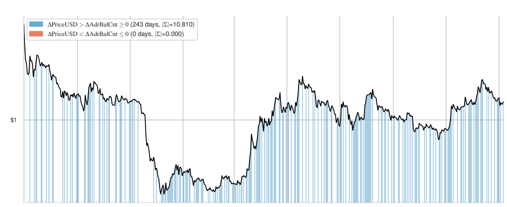
(c) ETH



(d) LTC



(e) XRP



(f) XTZ

Figure 2: Network effect observations and distribution (blue: positive NFX, red: reverse NFX, white: no NFX); userbase measured by total addresses with non-zero balance, value measured by USD token price.

punctuated by days/periods of no network effect observations during which the price either does not rise supra-proportionately to userbase or drops. In cryptoassets such as BTC and LTC, where userbase fluctuates, it is easier to notice the changes in network effects trends (blue and red lines in (a) and (d) in Figures 2 and 3), even through network effect frequency is comparable to ETH and XRP. Therefore, it is hard to conclude that in any cryptoasset network effects exhibit constant patterns that, if extended into the future, can hold predictive value. This does not mean that we do not acknowledge the exponential long-term price increase of some cryptoassets (Figure 1), but we note that this is not linked consistently to their userbase growth, which is what network effects theory suggests. One explanation of why our results do not support the conclusions of previous studies can relate to the different time frames. Most previous studies' datasets end around the valuation peak of January 2018, missing the precipitous fall in 2018 and the subsequent rise in 2019, which upend the relatively smoother network effect curves of valuations up until the end of 2017. Another explanation relates to methodology. For example, Peterson's revised study, which covers up to 2020 and confirms the finding of the paper's previous popular version that Bitcoin's valuation follows Metcalfe's law, excludes certain sizeable time periods, which, if accounted for, show a poor(er) fit [27]. A third explanation relates to the proxies used. Some previous studies rely on wallets (total addresses) as the proxy for userbase, which is a more crude measurement than our preferred addresses with non-zero balance, as the latter show only economically active users and are therefore a better approximation of relevant userbase.

(2) Reverse network effects are also noticeable meaning that cryptoassets are vulnerable to rapid decline, not just conducive to rapid growth: While network effects have mostly been used to describe growth patterns, they are equally applicable in describing decline. Reverse network effects reflect situations where a decrease in users is linked to a larger decrease in value. Such observations are important, because they show that each user loss incurs a greater loss of value and therefore expose the potential for a rapid decline of the network once user exodus begins. Reverse network effects therefore highlight the precariousness of success (as measured by proxies of value). Most cryptoassets exhibited at least one prolonged period where reverse network effects were dominant, during which phases their value contracted disproportionately to the contraction of their userbase ending up less valuable than their userbase size would otherwise suggest or mandate during that period. This is noticeable both when userbase is measured by addresses with non zero balance, but it is even more pronounced when userbase is measured as trailing 6-month active addresses (Figure 3). This makes sense since the users active in the trailing 6-month period are more likely to be responsive to price fluctuations compared to users who simply hold some balance on their account. From Figure 3 it is also evident that user disengagement is almost consistently observed after every price crash (as manifested through the reverse network effects that begin 6 months after many of the crashes), and the fact that price continues to decrease supra-proportionately to userbase, as measured by active users in the trailing 6-month period, 6 months after the crash, may be indicative of the lasting effects user exodus has on the value of cryptoasset networks. Generally, however, while reverse network effects serve as a cautionary note that rapid decline of value can be triggered by user exit, they are weaker in magnitude than positive network effects (Table 4). So, overall, positive network effects (albeit inconsistent) still seem to characterize cryptoasset networks.

(3) Cryptoassets do not seem to be a winner-take-all market: A common corollary of network effects is that they eventually cause the market to gravitate toward oligopolistic structure, since, everything else equal, users prefer to join the network where the value from their joining will be maximized. This causes a "rich-get-richer" effect where the most valuable network continues to become even more valuable as users prefer to join that over others. Such markets tend to become oligopolistic, with the usual downsides of such industry structure (higher prices, reduced output, entry barriers; lower variety and innovation), and can therefore be a cause for concern. For this to be more likely to happen the various networks (=cryptoassets) must be undifferentiated and switching among and multi-homing across networks must be rare or costly [29]. These features do not seem to characterize the cryptoasset market, which accordingly appears less susceptible to a winner-take-all trend, at least on account of network effects. Indeed, of the thousands of available cryptoassets many serve different purposes, and users can own multiple cryptoassets at the same time and enter and exit their networks without friction. As evidenced by our results, the fact that the various cryptoassets we studied exhibit network effects of comparable relative strength (Column 6 in Table 4), and that they retain their userbase and valuation cycles (Figure 1) seems to suggest that the underlying market features, including network effects, do not lead it toward an oligopolistic structure.

(4) Network effects strength across cryptoassets is comparable and therefore network effects do not accord a single cryptoasset a strong comparative advantage over its peers, undermining fears of concentration: Besides frequency and duration, i.e. what period of a cryptoasset's lifetime is dominated by network effects, another useful parameter of network effect observations in cryptoassets is their strength, i.e. the magnitude of the impact of a userbase change to value change [31]. Strong network effects can be indicative of higher homogeneity or cohesion within the network, where the addition of each new user (e.g. investor) affects existing users of that closely-knit network more than if it was a different looser network. In turn, this is reflected in the value of the network, or they may be indicative of stronger reputational effects, where the addition of each new user signals major changes for the network, which are then reflected in its value. Our results show that the comparative strength of network effects across the studied cryptoassets is similar (Table 4). This leads us to believe that no single cryptoasset benefits from network effects significantly more than its peers and therefore that no cryptoasset enjoys an overwhelming competitive advantage over its peers on account of network effects. A necessary corollary observation is that network effects accrue at similar levels to the studied cryptoassets, which means that network effects as a phenomenon, characterizes the cryptoasset industry as a whole (at least based on our sample), not just Bitcoin, which has been the main subject of many of extant studies in the area. This is not a surprising finding, but it is worth highlighting that it lends support to the previous point that the structure of the cryptoasset market does

not seem to be such where network effects lead it to concentration around a small number of cryptoassets or that it helps cryptoassets overtake their peers on account of network effects. This is most likely because cryptoassets are differentiated and multi-homing and switching are pervasive.

(5) Network effects are not consistently observed during the early days of cryptoassets and therefore it is doubtful that they can be relied on as a tool to bootstrap a new cryptoasset: A common business model when launching new products or services in digital markets is to exploit network effects to quickly establish a growing foothold. Particularly if the product or service is also the first of its kind to hit the market, network effects can dramatically augment the first mover advantage, everything else equal. Our results indicate that network effects are not consistently observed in the studied cryptoassets during their early days (the first year of data); in particular, DOGE, XTZ and LTC do not exhibit consistent positive network effects neither by token price (PriceUSD) nor by transaction value (TxTfrValAdjUSD) as proxies for value (Figures 2 and 5). The lack of consistency is even more pronounced when userbase is measured by active addresses in the trailing 6-month period, which is an instructive measure here, because it tracks recent user activity which is the driver of early adoption. In Figure 3 only BTC and ETH have a claim to positive early network effects and in ETH they are sparser. This suggests that new cryptoassets cannot necessarily hope that network effects will assist in their initial uptake. It is useful to dispel this hypothesis because investors are looking for patterns in events that may trigger valuation changes (e.g. the hypothesis that cryptoasset value as measured in monetary terms increases once the cryptoasset is listed on a major crypto-exchange).

(6) Comparison between network effects on price and transaction value reveals sensitivity to price, which can be a competitive disadvantage: Extant literature has relied exclusively on token price as the proxy for network value. Using transaction value too helps us draw useful comparisons. For this, it is most instructive to rely on trailing 6-month active addresses as the proxy for userbase, because this proxy is more responsive to value fluctuations. Then, a comparison between the strength of network effects measured by token price (PriceUSD) and by transaction value (TxTfrValAdjUSD) reveals that some cryptoassets experience greater fluctuations in their transaction value relative to their token price. During upturns, network effects tell us that token price and transaction value increase more than the userbase increases, and during downturns, reverse network effects show the opposite. By comparing the ratios among cryptoassets of the sum of network effects when value is measured by token price and the sum of network effects when value is measured by transaction value one can observe differences in how transaction value is affected among cryptoassets. Specifically, the ratios for BTC, DOGE, ETH and LTC are similar ranging from 0.12 to 0.14 for positive network effects and 0.07 to 0.09 for reverse network effects, whereas XRP's is 0.07 and for XTZ's is 0.06 for positive network effects and 0.04 and 0.03 for reverse network effects (compare sum ratios in Figure 3 and Figure 4). This means that during periods of positive network effects, XRP's and XTZ's transaction value grows more than their token price grows relative to their userbase, and that during periods of reverse network effects, XRP's and XTZ's transaction value drops more than their token price drops relative to their userbase. This kind of increased volatility may be generally undesirable, but it is particularly problematic during downturns (reverse network effects) because it shows that activity on XRP and XTZ networks is more drastically affected making them more sensitive and less resilient, which is a competitive disadvantage. Our results hold too when we look exclusively at 2017 and 2018 as the years with the most sustained price increase and decrease respectively.

7 CONCLUSION

Network effects can be among the most common and influential factors shaping market dynamics in industries where products and services are built around networks. It is no wonder that they have been cited as a determinant in how cryptoassets grow in value and how they compete. Our analysis shows that while network effects do characterize cryptoassets, they do not result in the usual concentration and competitive advantage implications usually associated with them. Our work also invites further research to determine the exact scope and conditions under which network effects apply. More precise proxies for userbase and value and accounting for exogenous effects are steps in the right direction. It will also be useful to re-run network effects analysis in the future as cryptoassets mature to observe whether network effects are a macroscopic determinant that simply needs more time to develop results; with only a decade of history behind them, cryptoassets may be too premature and fragmented a market to exhibit strong network effects.

REFERENCES

[1] 2007. Morgan Stanley / Visa International and Visa Europe. (Oct. 2007). https://ec.europa.eu/competition/antitrust/cases/dec_docs/37860/37860_629_1.pdf
[2] 2011. *Competition and Choice in Retail Banking - Ninth Report of Session 2010âĂŞ11.* Technical Report HC 612âĂŞI. House of Commons. https://publications.parliament.uk/pa/cm201011/cmselect/cmtreasy/612/612i.pdf
[3] Nick Arnosti and S Matthew Weinberg. 2018. Bitcoin: A Natural Oligopoly. In *10th Innovations in Theoretical Computer Science Conference*, Avrim Blum (Ed.). Vol. 124. Schloss Dagstuhl, 5.
[4] Daniel Birke and GM Peter Swann. 2004. Network effects in mobile telecommunications: An empirical analysis. *Journal of Evolutionary Economics* (2004), 65–84. Publisher: Citeseer.
[5] Bob Briscoe, Andrew Odlyzko, and Benjamin Tilly. 2006. Metcalfe's Law Is Wrong - Communications Networks Increase in Value as They Add Members But by How Much? *IEEE Spectrum* 43, 7 (July 2006), 34–39. https://doi.org/10.1109/MSPEC.2006.1653003
[6] Vitalik Buterin. 2014. On Bitcoin Maximalism, and Currency and Platform Network Effects. (Nov. 2014). https://blog.ethereum.org/2014/11/20/bitcoin-maximalism-currency-platform-network-effects/
[7] Jeffrey Church and Neil Gandal. 2005. Platform Competition in Telecommunications. In *The Handbook of Telecommunications Economics (Volume 2)*, Martin Cave, Sumit Kumar Majumdar, and Ingo Vogelsang (Eds.). North-Holland, 119–155.
[8] Jeffrey Church, Neil Gandal, and David Krause. 2008. Indirect network effects and adoption externalities. *Review of Network Economics* 7, 3 (2008). Publisher: De Gruyter.
[9] Jamil Civitarese. 2018. Does Metcalfe's Law Explain Bitcoin Prices? A Time Series Analysis. *SSRN Electronic Journal* (2018). https://doi.org/10.2139/ssrn.3107895
[10] Lin William Cong, Ye Li, and Neng Wang. 2020. *Tokenomics: Dynamic Adoption and Valuation.* Technical Report 27222. National Bureau of Economic Research.
[11] Don Cruickshank. 2000. *Competition in UK banking âĂŞ A Report to the Chancellor of the Exchequer.* Technical Report. The Stationery Office. 1206–1282 pages. http://www.hm-treasury.gov.uk/documents/financial_services/banking/bankreview/fin_bank_reviewfinal.cfm
[12] Bennett Cyphers. 2020. Visa Wants to Buy Plaid, and With It, Transaction Data for Millions of People. (Nov. 2020). https://www.eff.org/deeplinks/2020/11/visa-wants-buy-plaid-and-it-transaction-data-millions-people
[13] Nicholas Economides. 1996. The Economics of Networks. *International Journal of Industrial Organization* 14, 6 (Oct. 1996), 673–699. https://doi.org/10.1016/0167-7187(96)01015-6

[14] Nicholas Economides and Steven C. Salop. 1992. Competition and Integration Among Complements, and Network Market Structure. *The Journal of Industrial Economics* 40, 1 (March 1992), 105–123. https://doi.org/10.2307/2950629

[15] Joseph Farrell and Garth Saloner. 1985. Standardization, Compatibility, and Innovation. *The RAND Journal of Economics* 16, 1 (1985), 70. https://doi.org/10.2307/2555589

[16] John M. Gallaugher and Yu-Ming Wang. 2002. Understanding Network Effects in Software Markets: Evidence from Web Server Pricing. *MIS Quarterly* 26, 4 (Dec. 2002), 303. https://doi.org/10.2307/4132311

[17] Neil Gandal. 1995. Competing Compatibility Standards and Network Externalities in the PC Software Market. *The Review of Economics and Statistics* 77, 4 (1995), 599–608. https://doi.org/10.2307/2109809

[18] Neil Gandal and Hanna Halaburda. 2016. Can We Predict the Winner in a Market with Network Effects? Competition in Cryptocurrency Market. *Games* 7, 3 (2016), 16. https://doi.org/10.3390/g7030016

[19] Daniel D. Garcia-Swartz and Florencia Garcia-Vicente. 2015. Network effects on the iPhone platform: An empirical examination. *Telecommunications Policy* 39, 10 (Nov. 2015), 877–895. https://doi.org/10.1016/j.telpol.2015.07.011

[20] Andrei Hagiu and Simon Rothman. 2016. Network Effects ArenâĂŹt Enough. *Harvard Business Review* (April 2016), 64–71.

[21] Felix Irresberger, Kose John, and Fahad Saleh. 2020. The Public Blockchain Ecosystem: An Empirical Analysis. *SSRN Electronic Journal* (2020). https://doi.org/10.2139/ssrn.3592849

[22] Michael L. Katz and Carl Shapiro. 1985. Network Externalities, Competition, and Compatibility. *The American Economic Review* 75, 3 (1985), 424–440. https://www.jstor.org/stable/1814809

[23] Robert Metcalfe. 2013. Metcalfe's Law After 40 Years of Ethernet. *Computer* 46, 12 (Dec. 2013), 26–31. https://doi.org/10.1109/MC.2013.374

[24] Coin Metrics. 2020. Coin Metrics Hourly Reference Rates Methodology (version 2.5). (Nov. 2020).

[25] Daniel Perez, Jiahua Xu, and Benjamin Livshits. 2020. Revisiting Transactional Statistics of High-scalability Blockchains. 535–550.

[26] Timothy Peterson. 2018. Metcalfe's Law as a Model for Bitcoin's Value. *Alternative Investment Analyst Review* 7, 2 (2018), 9–18. https://doi.org/10.2139/ssrn.3078248

[27] Timothy Peterson. 2019. Bitcoin Spreads Like a Virus. *SSRN Electronic Journal* (2019). https://doi.org/10.2139/ssrn.3356098

[28] Jeffrey Rohlfs. 1974. A Theory of Interdependent Demand for a Communications Service. *The Bell Journal of Economics and Management Science* 5, 1 (1974), 16–37. https://doi.org/10.2307/3003090

[29] Richard Schmalensee. 2011. Jeffrey RohlfsâĂŹ 1974 Model of Facebook: An Introduction. *http://ssrn.com/abstract=1802053* (2011).

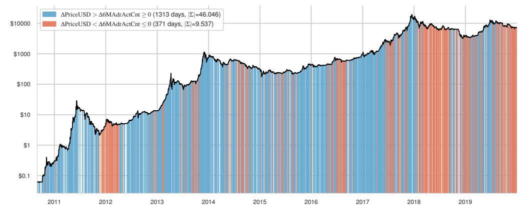
[30] Savva Shanaev, Satish Sharma, Arina Shuraeva, and Binam Ghimire. 2019. The Marginal Cost of Mining, Metcalfe's Law and Cryptocurrency Value Formation: Causal Inferences from the Instrumental Variable Approach. *SSRN Electronic Journal* (2019). https://doi.org/10.2139/ssrn.3432431

[31] Venkatesh Shankar and Barry L. Bayus. 2003. Network effects and competition: an empirical analysis of the home video game industry. *Strategic Management Journal* 24, 4 (April 2003), 375–384. https://doi.org/10.1002/smj.296

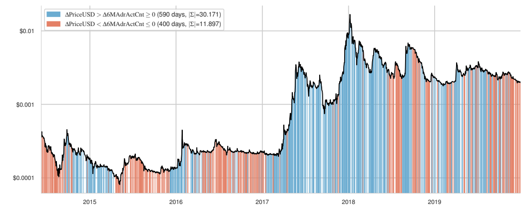
[32] G. M. Peter Swann. 2002. The Functional Form of Network Effects. *Information Economics and Policy* 14, 3 (Sept. 2002), 417–429. https://doi.org/10.1016/S0167-6245(02)00051-3

[33] Ben Van Vliet. 2018. An Alternative Model of MetcalfeâĂŹs Law for Valuing Bitcoin. *Economics Letters* 165 (2018), 70–72. https://doi.org/10.1016/j.econlet.2018.02.007

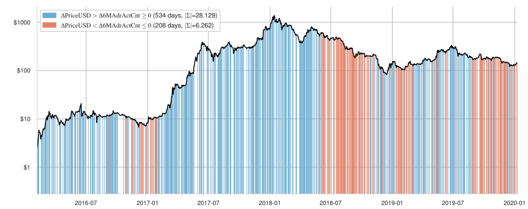
8 APPENDIX



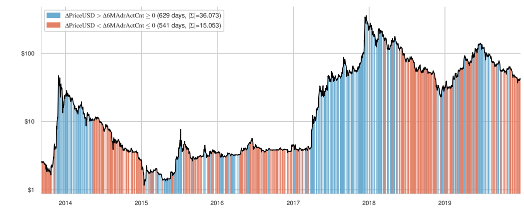
(a) BTC



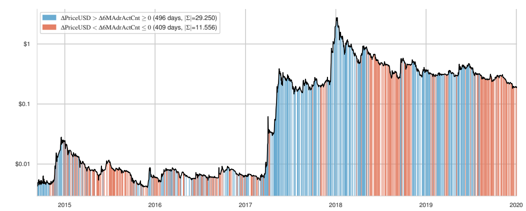
(b) DOGE



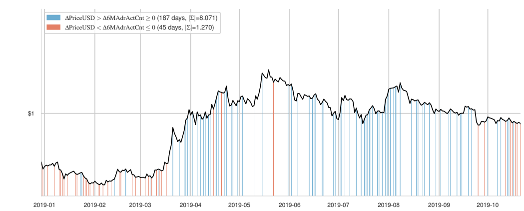
(c) ETH



(d) LTC

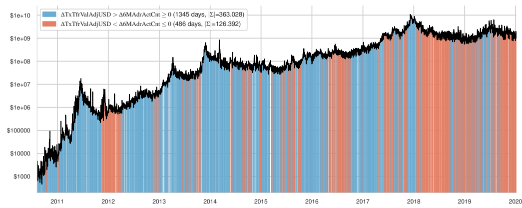


(e) XRP

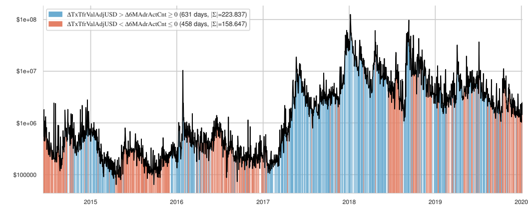


(f) XTZ

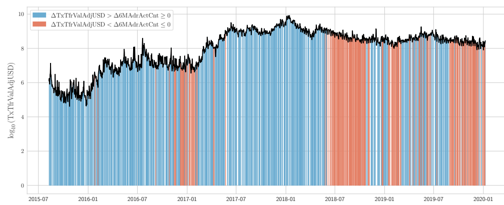
Figure 3: Network effect observations and distribution (blue: positive NFX, red: reverse NFX, white: no NFX); userbase measured by trailing 6 month addresses, value measured by USD token price.



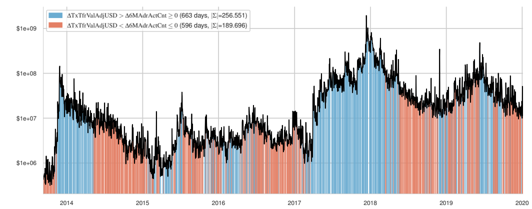
(a) BTC



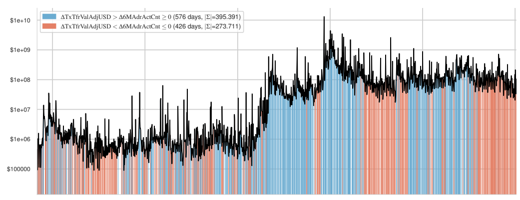
(b) DOGE



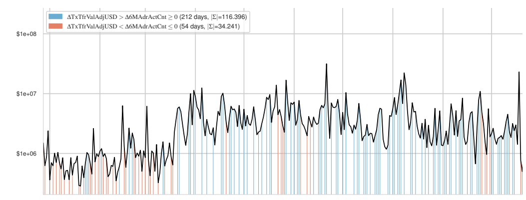
(c) ETH



(d) LTC

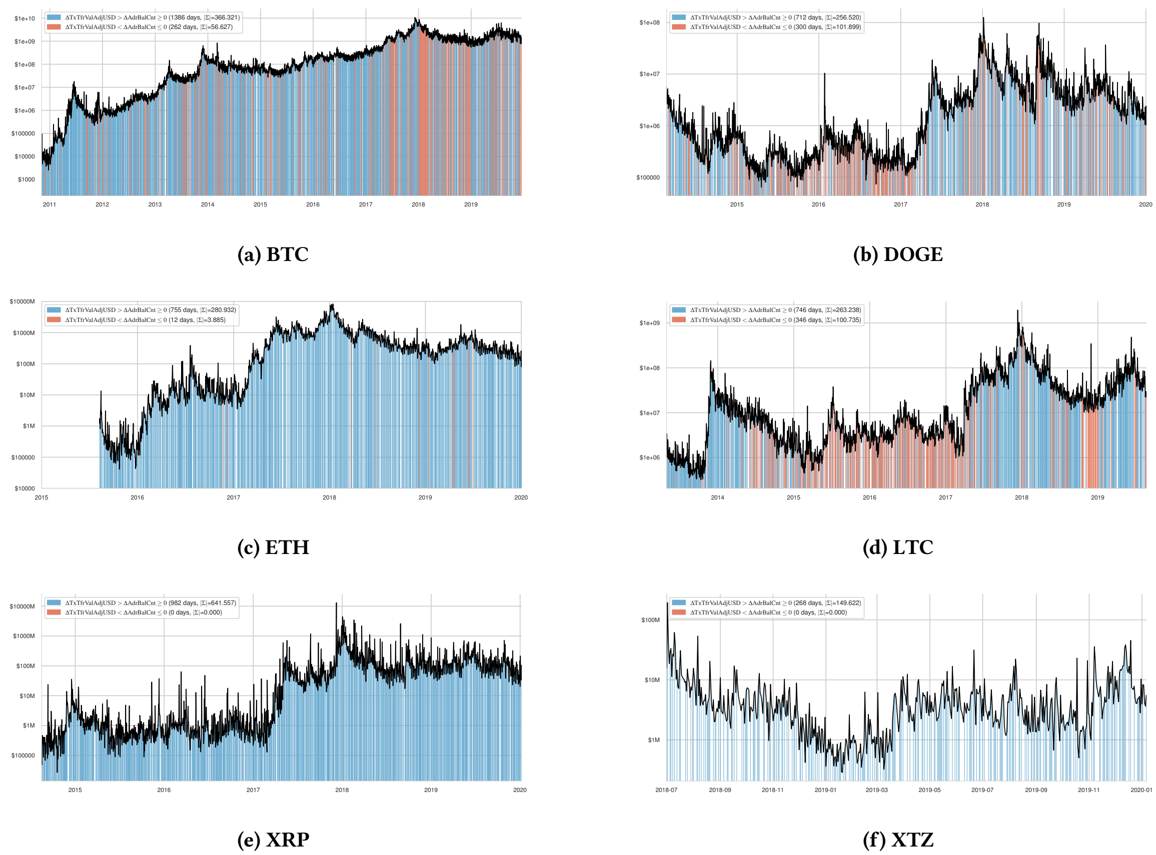


(e) XRP



(f) XTZ

Figure 4: Network effect observations and distribution (blue: positive NFX, red: reverse NFX, white: no NFX); userbase measured by trailing 6 month addresses, value measured by transaction value.



(a) BTC

(b) DOGE

(c) ETH

(d) LTC

(e) XRP

(f) XTZ

Figure 5: Network effect observations (blue: positive NE, red: reverse NE, white: no NE); userbase measured by total addresses with non-zero balance, value measured by transaction value.

Discussion Paper #2

Blockchain Hash, the Missing Axis of the Accounts to Settle the Triple Entry Bookkeeping System

Alessio Faccia, Coventry University

Narcisa Roxana Moşteanu, American University of Malta

Luigi Pio Leonardo Cavaliere, Università di Foggia

Abstract

The bookkeeping accounting method recognized all over the world is based on the so-called double entry, with which in each account (defined T-Account for its shape) there are two sections, Debit and Credit. These two sections take on different meanings depending on the nature of each account. The double entry is an exceptional consolidated accounting method that dates back to the fifteenth century, however it has highlighted limits in terms of auditing. The single entry did not take into account the cross relations between the accounts, reporting only on the journal. The double entry has overcome this limit by introducing the ledger, but a cross-check of the mirrored transactions recorded by the other companies is still missing. The introduction of blockchain technology could now offer a new opportunity to ensure further auditing control. The transition from double entry to triple entry is therefore only a matter of time. The blockchain itself is borrowing the word "ledger" from accounting and now it is time for accounting to introduce a third leg (another axis) to the T-Accounts, that can be turned into a new X-shaped version of accounts. This third axis can be used to include the unique identifier of each transaction represented by the Hash.

Keywords: Triple Entry, Blockchain, Accounting, Bookkeeping, Shared Ledger.

Blockchain hash, the missing axis of the accounts to settle the triple entry bookkeeping system

Dr. Alessio Faccia
Coventry University
Priory St. – CV15FB
Coventry, UK
+44 7425277726
University College London Centre for Blockchain Technologies (UCL CBT)
https://orcid.org/0000-0001-7231-6774
alessio.faccia@gmail.com

Prof. Narcisa Roxana Moşteanu
American University of Malta
Triq Dom Mintoff, BML1013
Bormla, Malta
+356.99655651
https://orcid.org/0000-0001-5905-8600
narcisamosteanu@yahoo.com

Mr. Luigi Pio Leonardo Cavaliere
Università di Foggia
Via Romolo Caggese, 1, 71121
Foggia FG, Italy
+39.3895739195
https://orcid.org/0000-0003-3169-567X
luigi.cavalie@gmail.com

ABSTRACT

The bookkeeping accounting method recognized all over the world is based on the so-called double entry, with which in each account (defined T-Account for its shape) there are two sections, Debit and Credit. These two sections take on different meanings depending on the nature of each account. The double entry is an exceptional consolidated accounting method that dates back to the fifteenth century, however it has highlighted limits in terms of auditing. The single entry did not take into account the cross relations between the accounts, reporting only on the journal. The double entry has overcome this limit by introducing the ledger, but a cross-check of the mirrored transactions recorded by the other companies is still missing. The introduction of blockchain technology could now offer a new opportunity to ensure further auditing control. The transition from double entry to triple entry is therefore only a matter of time. The blockchain itself is borrowing the word "ledger" from accounting and now it is time for accounting to introduce a third leg (another axis) to the T-Accounts, that can be turned into a new X-shaped version of accounts. This third axis can be used to include the unique identifier of each transaction represented by the Hash.

CCS Concepts

• **Applied Computing → Law, Social and behavioral sciences → Economics.**

Keywords

Triple Entry; blockchain; accounting; bookkeeping; shared ledger.

1. INTRODUCTION

The double entry accounting methodology, scientifically formalized in Luca Pacioli's book [1] at the end of the fifteenth century, has been in use for more than half a millennium so far. Numerous accounting studies have refined the bookkeeping technique, however the basic structure, consisting of the two Debit and Credit sections of each account, along with the use of Ledger and Journal, has always remained the same. The use of this specific (accounting) language has numerous benefits and it is no coincidence that it is still in use today. The digitization of all the processes that took place at the end of the twentieth century [2], however, greatly facilitated the process of reporting and accounting for transactions, thanks to specific software known as Accounting Information Systems, then integrated with other managerial functions, which determined the birth of the so-called Management Information Systems (MIS), up to the inclusion of further engineered functions that led to the availability of Enterprise Resource Planning Systems (ERPs) [3-5]. The introduction of blockchain technology which, especially in the last decade has been the subject of particular attention and discussion by scholars, but also and above all by companies and the public sector. In this research it is assumed that readers know at least the basic elements of the blockchain (Node, Transaction, Hash, Ledger, Block), its general functioning (a chain of blocks of information shared by all users), but above all the its advantages (Decentralization; Transparency; Security; Immutability; Consent; Responsibility; Programmability). Given this assumption, it is possible to consider the blockchain as a new paradigm, rather than a technology [6].

2. METHODOLOGY

The methodology used in this research falls within the broadest meaning of qualitative analysis, but can at the same time be identified in applied research as it aims and proposes a practical application of the model devised. Starting from a brief historical analysis of the ideas related to the application of the triple game, the authors show an alternative way with the creation of a new system, also demonstrating its effective applicability.

3. LITERATURE REVIEW

The analysis of the existing literature in which this research is rooted can be identified in two different strands, that relating to previous studies relating to the so-called "triple entry" and those relating to the possible applications of the blockchain in accounting. Although some researchers have attempted to combine these two strands of study, no one has so far been able to combine them effectively.

3.1. Triple Entry Accounting

At least three main authors who have theorized, in alternative ways, the so-called triple entry bookkeeping can be identified. Therefore, each of them proposed very dissimilar systems, in different periods and geographic areas. Therefore, identifying what the third entry might be can become rather confusing.

3.1.1. Fedor Esersky

The Russian researcher Fedor Esersky [7-9] named triple-entry (also known as the "Russian Triple-Entry") at the end of the 20th century, suggesting the use of three accounting books: 1) chronological entry, 2) systematic accounts, and 3) summary of accounts. The author intended to overcome one of the limitations of the double-entry system by constantly updating of inventory, rather than doing it only at the end of the period, avoiding a lag between existing goods in the warehouse and their value in the accounting books after each sale transaction. Therefore, it would be more appropriate to define the system identified by Esersky as a “triple book” rather than a “triple entry”.

3.1.2. Yuji Ijiri

The Japanese professor Yuji Ijiri, in the 80s of the last century, suggested the introduction of a third axis, called "force", in order to identify not only the income, but also the wealth, that can differ from the income. This system, defined by the author as "momentum accounting", also intends to measure changes in the flows of accounts, considered as a "force" measure to highlight the extent of the changes that occurred in the accounts in the periods. The "momentum accounting" system, unlike Esersky’s, therefore proposes only the introduction of a third axis, but not also that of a third accounting book [9-10].

3.1.3. Ian Grigg

The researcher, consultant and entrepreneur Ian Grigg first determined a useful application of the so-called “Ricardian Contract” in the modern systems, and then merging cryptography and bookkeeping, suggested a triple entry system, eliminating reconciliation and allowing accounts to be shared. According to Grigg, a triple entry bookkeeping can be defined as “*recordkeeping for two or more parties through a shared transaction repository (STR) with a “signature – signature – signature” structure*” [10-11], in which the transaction is stored in a shared repository only once all the signatures are made by the involved parties. Grigg also suggested that a further copy of the STR (shared transaction repository) could be prepared “*as a subledger to the general ledger of transactional parties*”. The system devised by Grigg, similarly to Esersky, focuses again on the creation of a new book, in this case a shared ledger (rather than that related to the inventory identified by the Russian author), but appears to be missing a third axis where the signatures can be stored.

3.1.Blockchain Accounting

Blockchain technology has become popular in recent years thanks to Bitcoin, with which it is often confused; this technology, which is the tool behind cryptocurrencies, is not easy to define, due to the many technicalities that characterize it. Blockchain represents a new way of managing information that guarantees the immutability of the data within it and certifies the history of all data and all operations connected to each transaction. The peculiarity of the blockchain consists in the absence of a professional intermediary who must guarantee the truthfulness of the data. This task, in fact, is performed by the participants themselves to the blockchain through an authentication system. In addition, any transaction stored in the chain cannot be canceled or modified, and remains accessible at any time by members of the network. The transactions to which blockchain technology can be applied are, ideally, all those involving multiple subjects: from payments, to the management of information related to contracts (such as smart contracts), to transactions that concern the exchange of goods and services, besides many others. The potentially affected sectors are therefore multiple: from banking to insurance, from energy to healthcare, without excluding the telecommunications sector. The advantages of using blockchain and smart contracts in administrative-accounting consultancy are demonstrated by the initiatives launched by the so-called Big Four Auditing companies: Deloitte, Ernst and Young, KPMG and PriceWaterhouseCooper. Several researchers have argued that blockchain-based accounting is the next step for the accounting industry. Ultimately, the blockchain is the architecture that lends itself to be the environment on which to base the new accounting system proposed by Grigg and which has become necessary with the recent financial events that push towards decentralized and distributed management of trust. There are two characteristics that identify the architecture of the DLT as a tool through which to modernize one of the oldest professions in the world: a) the immutability of the register; b) transparency of transactions [3-11]. The necessary consent (the absolute majority of the nodes) to insert the new blocks in the register, the consequent unchangeability of the block and the so-called “Proof-of-Work” makes the blockchain immutable and suitable for a profession where precision must be the indispensable requirement. Furthermore, given that the register can be consulted by a more or less vast community, transactions can be traced and known by the public of users who have interest in the performance of the company. Blockchain technology meets all the legal requirements and accounting standards, above all the ban on canceling the already recorded transactions. Since transactions cannot be eliminated from the blockchain (in case of modification of an incorrect block, the node must insert a new block that corrects the previous one), the readability of the accounting entries is best satisfied.

4. FINDINGS AND CONCLUSIONS

Despite the large number of studies and researchers who have dealt with this matter, it is believed that we can offer a decisive contribution with the present research. An effective application of the blockchain, that could be useful also for auditing purposes, therefore, as recently demonstrated by Ian Grigg, requires the use of cross signatures before storing any transaction in a shared ledger. The system suggested by Grigg, although suggesting a signature for each transaction to be stored in the ledger, does not take into consideration the need to add another axis to the accounts, as it is intended to be demonstrated in this research. The need to add a new axis to the accounts appears to be a natural consequence of being able to cross-identify (and armor) each transaction, not only in two ways to balance the accounts in the double entry system of the company, but also to guarantee perfect mirroring of the transaction towards the external party with whom the transaction itself takes place (see Figure 1) [9-11].

Figure 1. The Evolution of Triple Entry.

Adding a new axis to an account also entails a necessary modification of its shape, which can no longer be represented only by the traditional “T”, but by a more complex “X” shape to allow the identification of the heading at the top, Debit and Credit, respectively at the left and at the right sides, and, last but not least at the bottom the third axis will be the hash, from time to time obtained in each transaction, to be connected to the values recorded in Debit or Credit (see Figure 2).

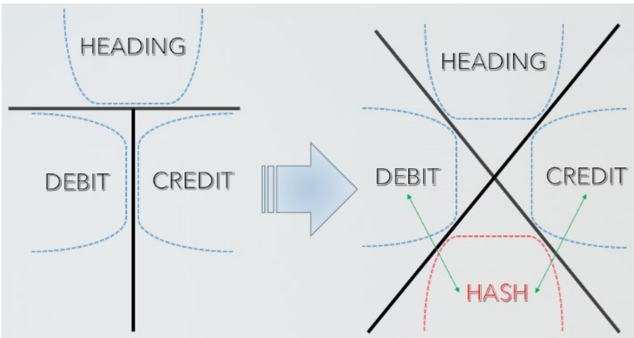


Figure 2. From T-Accounts to X-Accounts.

Given the nature of accounts as it is shown in Figure 3, the double entry bookkeeping system can be always considered valid and useful for the transaction recording, although integrated by the third hash entry [12].

For a better understanding by non-accountants of the transactions under a double entry system, it is considered necessary to highlight that the words “Debit” and “Credit” have no intrinsic meaning, but only indicate, respectively, the left and right section of the account. The meaning of the amounts entered in each section depends on the nature attributed to each account, as shown in Figure 3 [12].

Let us consider the following case study (see Figure 4).
“Test Company Ltd” carries out the following transactions:
1) 01.01.2020 £ 1,000 revenue accrual for services rendered to “Customer Ltd”;
2) 05.01.2020 £ 600 bank collection from “Customer Ltd”;
3) 31.01.2020 £ 250 rent payment (by bank) to “Landlord Ltd”;
4) 02.02.2020 £ 50 cash withdrawal.
For greater completeness of information, the nature of each account will be indicated in order to understand the meaning attributed from time to time by the different sections of the accounts. This is essential to understand the balanced (and mirrored) system and why the amounts should be entered in the left or right section of each account.
Assuming that all three companies (Test Company Ltd, Customer Ltd, and Landlord Ltd) have their bank accounts in different banks, we can identify in this case 6 different entities that must access an integrated system (on the blockchain platform) to mutually approve only those transactions in which they participate directly.
As can be clearly observed in Figure 3, each transaction follows the rules of the double entry, however a numbered link is added to each transaction (in addition to the date on which it is carried out), relative to the hash, a unique identifier that is assigned to that specific one transaction.
Among all six entities that are considered in the case, not all (apart from the Test Company Ltd) are always involved in the approval of all transactions, but only in those that are relevant to them. The approval of the transactions should take place by affixing a digital signature (through a smart card, a digital token, or a biometric or similar device) with consequent automatic affixing also of a time stamp. In a similar scenario, for reasons of control (corporate governance), of internal and external cross-checking (internal and external auditing), the rule of separation of duties must be necessarily applied (as also indicated in general by the COSO Framework), therefore the accounting office will only take care of accounting recording, while another office (e-procurement), duly delegated by the company administrator, will deal with the validation and digital signature of the transactions to have the hash attributed, even if asynchronously with respect to the accounting recording.

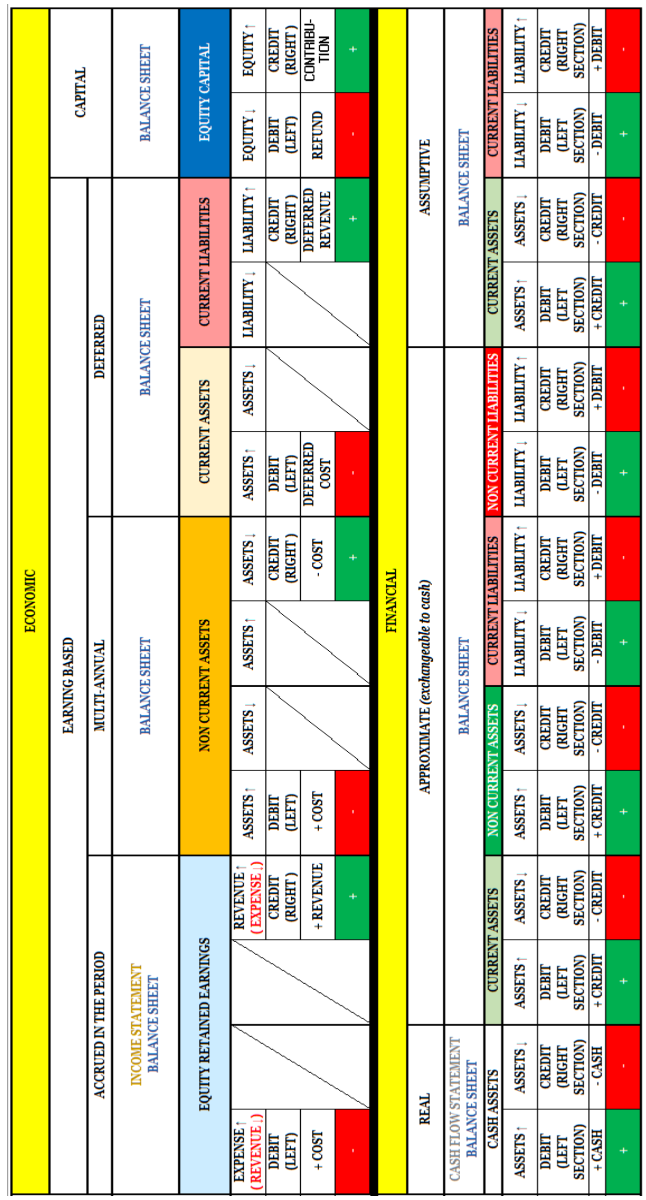


Figure 3. Nature of accounts. *Source:* [12]

By analyzing the individual transactions, the relevant subjects (see Figure 5) for the simultaneous approval of each of them are identified.

- **Transaction 1)** services rendered: Test Company Ltd – Customer Ltd;
- **Transaction 2)** receivable collection: Test Company Ltd – Customer Ltd – Bank 1 – Bank 2;
- **Transaction 3)** rent payment: Test Company Ltd – Landlord Ltd – Bank 1 – Bank 3
- **Transaction 4)** cash withdrawal: Test Company Ltd – Bank 1

Considering that the hash can be attributed only and exclusively if all the entities involved in the specific transaction approve it by affixing a digital signature (and the related time stamp), in the event that an entity does not affix it, it could be immediately (from an auditing perspective) to focus attention first on those transactions with the missing hash. The lack of hash in fact could alternatively configure two situations: a) negligence or delay of one of the entities involved for the affixing of the digital signature; b) identification of errors, by one of the entities, which rightly refuses to confirm the transaction. The lack or delay in obtaining the hashes (which an occur asynchronously), does not generate any problem from an accounting perspective, as the recording process can

TEST COMPANY Ltd.

ACCOUNT RECEIVABLE

FINANCIAL > APPROXIMATE > CURRENT ASSET	
+ ASSETS ↑ (+ Credit)	ASSETS ↓ (- Credit) -
DEBIT	CREDIT
1 01.01.2020 £ 1,000.00	£ 600.00 05.01.2020 2

HASH		
1	o1a2b3c4d5e6f7g8h9i	01.01.2020
2	0h9i8j7k6l5m4n3o2p1	05.01.2020

SERVICE REVENUE

ECONOMIC > ACCRUED IN THE PERIOD > RETAINED EARNINGS	
	REVENUE ↑ EQUITY ↑ +
DEBIT	CREDIT
	£ 1,000.00 01.01.2020 1

HASH		
1	o1a2b3c4d5e6f7g8h9i	01.01.2020

BANK ACCOUNT

FINANCIAL > REAL > CASH CURRENT ASSET	
+ ASSETS ↑ (+ Cash)	ASSETS ↓ (- Cash) -
DEBIT	CREDIT
2 05.01.2020 £ 600.00	£ 250.00 31.01.2020 3
	£ 50.00 02.02.2020 4

HASH		
2	0h9i8j7k6l5m4n3o2p1	05.01.2020
3	111aaa222bbb333ccc	31.01.2020
4	444ddd555eee666fff	02.02.2020

RENT EXPENSE

ECONOMIC > ACCRUED IN THE PERIOD > RETAINED EARNINGS	
+ EXPENSE ↑ EQUITY ↓	
DEBIT	CREDIT
3 31.01.2020 £ 250.00	

HASH		
3	111aaa222bbb333ccc	31.01.2020

CASH

FINANCIAL > REAL > CASH CURRENT ASSET	
+ ASSETS ↑ (+ Cash)	ASSETS ↓ (- Cash) -
DEBIT	CREDIT
3 31.01.2020 £ 50.00	

HASH		
4	444ddd555eee666fff	02.02.2020

BANK 1

DEPOSITS (TEST COMPANY Ltd)

FINANCIAL > REAL > CASH CURRENT ASSET	
+ ASSETS ↑ (+ Cash)	ASSETS ↓ (- Cash) -
DEBIT	CREDIT
2 31.01.2020 £ 250.00	£ 600.00 05.01.2020 1
3 02.02.2020 £ 50.00	

HASH		
1	0h9i8j7k6l5m4n3o2p1	05.01.2020
2	111aaa222bbb333ccc	31.01.2020
3	444ddd555eee666fff	02.02.2020

CUSTOMER Ltd.

ACCOUNT PAYABLE

FINANCIAL > APPROXIMATE > CURRENT LIABILITIES	
+ LIABILITY ↓ (- Debit)	LIABILITY ↑ (+ Debit) -
DEBIT	CREDIT
2 05.01.2020 £ 600.00	£ 1,000.00 01.01.2020 1

HASH		
1	o1a2b3c4d5e6f7g8h9i	01.01.2020
2	0h9i8j7k6l5m4n3o2p1	05.01.2020

SERVICE EXPENSE

ECONOMIC > ACCRUED IN THE PERIOD > RETAINED EARNINGS	
+ EXPENSE ↑ EQUITY ↓	
DEBIT	CREDIT
1 01.01.2020 £ 1,000.00	

HASH		
1	o1a2b3c4d5e6f7g8h9i	01.01.2020

BANK ACCOUNT

FINANCIAL > REAL > CASH CURRENT ASSET	
+ ASSETS ↑ (+ Cash)	ASSETS ↓ (- Cash) -
DEBIT	CREDIT
	£ 600.00 05.01.2020 2

HASH		
2	0h9i8j7k6l5m4n3o2p1	05.01.2020

BANK 2

DEPOSITS (CUSTOMER Ltd)

FINANCIAL > REAL > CASH CURRENT ASSET	
+ ASSETS ↑ (+ Cash)	ASSETS ↓ (- Cash) -
DEBIT	CREDIT
1 05.01.2020 £ 600.00	

HASH		
1	0h9i8j7k6l5m4n3o2p1	05.01.2020

LANDLORD Ltd.

RENT REVENUE

ECONOMIC > ACCRUED IN THE PERIOD > RETAINED EARNINGS	
	REVENUE ↑ EQUITY ↑ +
DEBIT	CREDIT
	£ 250.00 31.01.2020 1

HASH		
1	111aaa222bbb333ccc	31.01.2020

BANK ACCOUNT

FINANCIAL > REAL > CASH CURRENT ASSET	
+ ASSETS ↑ (+ Cash)	ASSETS ↓ (- Cash) -
DEBIT	CREDIT
2 05.01.2020 £ 250.00	

HASH		
1	111aaa222bbb333ccc	31.01.2020

BANK 3

DEPOSITS (LANDLORD Ltd)

FINANCIAL > REAL > CASH CURRENT ASSET	
+ ASSETS ↑ (+ Cash)	ASSETS ↓ (- Cash) -
DEBIT	CREDIT
	£ 250.00 31.01.2020 1

HASH		
1	111aaa222bbb333ccc	31.01.2020

Figure 4. X-Accounting Case Study.

continue to be made according to the double entry system. Missing hashes can be added later (without creating delays in the accounting chronological recording) or cause adjustments to incorrect recordings [14-15].

The advantages deriving from such a system would therefore be evident both with regard to auditing (avoiding fraud such as those that occur through the invention of false invoices or unjustified

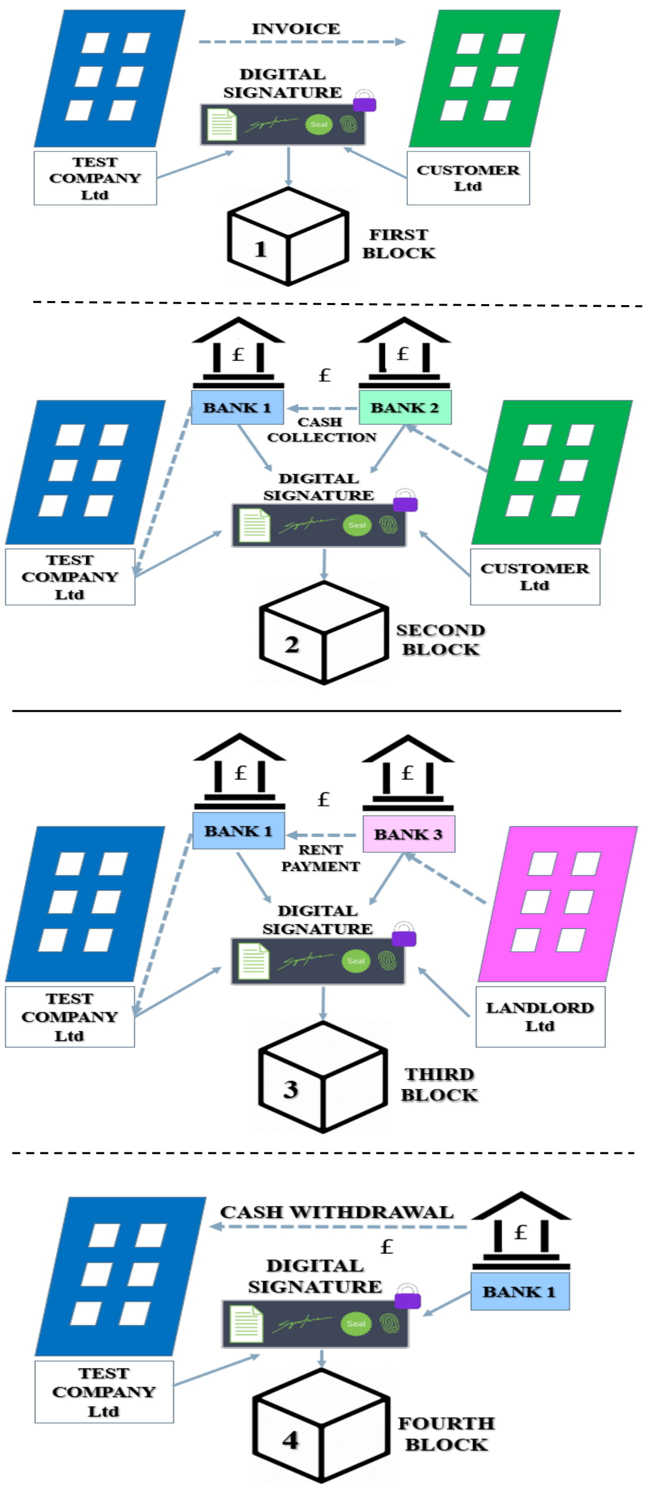


Figure 5. X-Accounting Blockchain signature process.

increase in revenues), and from a corporate governance perspective in terms of processes, requiring different cross-checks both internally (between different departments of the same company such as accounting and e-procurement) and externally, with a mirrored cross-check with the counterparties of the transactions.

The demonstration just carried out of a practical application of accounting integrated in a blockchain system constitutes the first empirical evidence of the feasibility of exceeding the limits of the double entry. The integration of this system now seems desirable, but above all a greater dialogue between engineers and accounting and finance experts. It is necessary to have a financial literacy of the IT engineers to understand the operation of the transactions, equally obvious is the need for the accountants to have to know the technologies underlying the system just described.

5. LIMITATIONS

The main limitations that can be identified for this research are essentially two: a) the application is proposed only in theory, as it would be necessary to develop and codify a suitable software to integrate accounting with the third axis and at the same time generate a hash shared in every transaction; b) as this is an early stage study, potential cryptographic or privacy issues have so far been neglected.

6. ACKNOWLEDGEMENTS

The contribution of the authors in this research can be distributed as follows: Dr. Alessio Faccia is the author of the main idea of X-Accounting with the introduction of the third axis in the accounts, he has therefore prepared an introduction, findings and conclusions; Professor Narcisa Roxana Moşteanu decided the best methodology and dealt with the preparation of the literature review, as well as supervising the editing and revision of the research; Mr. Luigi Pio Leonardo Cavaliere provided decisive support for the search for the necessary references used in the research.

7. REFERENCES

[1] Pacioli, L. 1494. Summa de arithmetica, geometria. Proportioni et proportionalita.

[2] Mosteanu, N. R., Faccia, A. 2020. Digital Systems and New Challenges of Financial Management-FinTech, XBRL, Blockchain and Cryptocurrencies. Calitatea – *Quality-Access to Success*, *21*(174).

[3] Faccia, A., Mosteanu, N. R., Fahed, M., Capitanio, F. 2019. Accounting Information Systems and ERP in the UAE: An Assessment of the Current and Future Challenges to Handle Big Data. *ACM Proceedings of the 2019 3rd International Conference on Cloud and Big Data Computing* (pp. 90-94).

[4] Faccia, A. 2019. Data and Information Flows: Assessing Threads and Opportunities to Ensure Privacy and Investment Returns. ACM *Proceedings of the 2019 3rd International Conference on Cloud and Big Data Computing* (pp. 54-59).

[5] Faccia, A., Al Naqbi, M. Y. K., & Lootah, S. A. 2019. Integrated Cloud Financial Accounting Cycle: How Artificial Intelligence, Blockchain, and XBRL will Change the Accounting, Fiscal and Auditing Practices. ACM *Proceedings of the 2019 3rd International Conference on Cloud and Big Data Computing* (pp. 31-37).

[6] Tasca, P. 2019. Insurance under the blockchain paradigm. In Business Transformation through Blockchain (pp. 273-285). *Palgrave Macmillan*, Cham.

[7] Irson, C. 2016. Partie Triple. *Dictionnaire historique de comptabilité des entreprises*, 393.
[8] Bychkova, S., & Smirnova, I. A. 1998. Differences and similarities in Russian and Western approaches to auditing standard. *British Accounting Association Conference*.
[9] Faccia, A., Moşteanu, N. R. 2019. Accounting and Blockchain technology: from double-entry to triple-entry. *The Business & Management Review*, 10(2), 108-116.
[10] Ibañez, J. I., Bayer, C. N., Tasca, P., & Xu, J. (2020). REA, Triple-Entry Accounting and Blockchain: Converging Paths to Shared Ledger Systems. Available at SSRN.
[11] Grigg, I. 2005. Triple entry accounting. *Systemics Inc*.
[12] Faccia, A., Mosco, D. 2019. Understanding the Nature of Accounts Using Comprehensive Tools to Understand Financial Statements. *Financial Markets, Institutions and Risks*, 3(3), 18-27.
[13] COSO - Committee of Sponsoring Organizations of the Treadway Commission. 2017. Enterprise Risk Management - Integrated Framework
[14] Faccia, A., Moşteanu, N. R. 2019. Tax evasion - information system and Blockchain. *Journal of Information Systems & Operations Management*, 13(1), 65-74.
[15] Schmitz, J., & Leoni, G. 2019. Accounting and auditing at the time of blockchain technology: a research agenda. *Australian Accounting Review*, 29(2), 331-34

Discussion Paper #3

Network Effects and Market Concentration for Blockchain-based Decentralized Assets

Olaoluwa Samuel-Biyi

Industry Associate

UCL Centre for Blockchain Technologies

Abstract

Network effects exist when the value of a product increases as the number of users increase. For network sponsors, strong positive network effects result in market concentration and increase their market power. These effects also exist for decentralized networks such as the network for blockchain-based digital assets; however, in these markets, there are no centralized sponsors and market power is distributed in the hands of the participants. For decentralized digital assets, network effects are unlikely to result in a winner-take-all outcome, and multiple digital assets can remain viable in the long-run. These markets also prevents rent-seeking and are inherently more efficient

Keywords: Switching Costs, Network Effects, Blockchain, Decentralized Assets.

Network Effects and Market Concentration for Blockchain-based Decentralized Assets

Olaoluwa Samuel-Biyi

Abstract:

Network effects exist when the value of a product increases as the number of users increase. For network sponsors, strong positive network effects result in market concentration and increase their market power. These effects also exist for decentralized networks such as the network for blockchain-based digital assets; however, in these markets, there are no centralized sponsors and market power is distributed in the hands of the participants. For decentralized digital assets, network effects are unlikely to result in a winner-take-all outcome, and multiple digital assets can remain viable in the long-run. These markets also prevent rent-seeking and are inherently more efficient.

Index Terms: Switching Costs, Network Effects, Blockchain, Decentralized Assets

INTRODUCTION

A product or service exhibits positive network effects if the benefits of its usage increase as the number of users increase. In economic terms, this is also known as demand-side economies of scale. This phenomenon can be observed across many industries like communications (Oren & Smith, 1891), payments (Leibbrandt, 2004), gaming (Shankar et al., 2002) and social media (Qiu et. al, 2015), where the benefit of consumption is influenced by the size of the network of consumers. In telecommunications, for example, a user only derives value from joining the network if their immediate circle and other potential contacts are also easily accessible via the network or other compatible ones. Strategy literature has extensively analysed the role of network effects in delivering competitive advantage to network sponsors (see Katz & Shapiro, 1985), and both researchers and practitioners have studied how companies deploy strategies to create and reinforce these effects in order to gain and protect market share (Tucker, 2018). In most cases, network sponsors perpetuate network effects by deploying tactics which will increase switching costs for users. These tactics could involve product pricing, e.g., through penetrative pricing--negatively tagged "bargain-then-rip-off" (Farrell et al., 2006; Westarp et al., 2000)—or they could be through product development by ensuring incompatibility with competitors' products.

For consumers, switching costs are the costs associated with switching from one product, brand or system to another. These are commonly monetary costs, but they can also be intangible costs like time, effort, learning costs and other psychological barriers (Burnham et al., 2003). Acting rationally, consumers would assess the benefits from switching to be positive net of the costs; consequently, where product qualities cannot be significantly differentiated or improved over competitors', sponsors or promoters attempt to increase switching costs to preserve their market advantage. Switching costs function to reinforce network effects (and vice versa) in industries where they apply; as network effects strengthen, the opportunity cost of transitioning to a less robust network itself becomes a significant switching cost.

Management literature has mostly examined network effects in the context of sponsor agents interested in appropriating monopoly benefits, and the role of switching costs in the process. The effect of compatibility between competing products and standardization to enable complimentary products in the aggregation of network effects and its externalities have also been well-researched (see Besen & Farrell, 1994). Farrell et al. (2006) have examined policy implications for high switching costs in order to prevent a winner-take-all outcome that might create sub-optimal market welfare outcomes, for example, via legislation in favour of cross-network compatibility between large and small competitors. However, as the field is still nascent, research is light on describing the development of network effects in the context of decentralized assets and systems, where there are no sponsor agents and where the value from network effects does not accrue monopolistic profits to any single entity. Furthermore, little is explained about the implications for network effect development where there are multiple competing products which are compatible in these decentralized marketplaces.

Blockchain-based digital assets are an emerging class of assets, a foundational subclass of which are decentralized in nature. Decentralized digital currencies like Bitcoin, for example, have a network of users who benefit increasingly as the size of the user network grows. These benefits vary according to the utility to the holder. For users interested in its use-case as a currency or payment instrument, more users on the network imply broader acceptability, better liquidity and legitimacy. Likewise, for speculators and users interested in the asset as a store of value, increasing usage ensures price stability or appreciation. The pricing power and governance framework of the Bitcoin asset on the network is not within the remit of any single agent; it is determined by the push and pull of demand and supply in the market, and consensus of participants respectively.

The technical barrier to entry for the creation of other digital assets that could compete with Bitcoin's use-cases is extremely low, and many competing blockchain networks such as Ethereum have emerged and developed their own network of users in parallel. The motivation for participating in these alternative blockchain networks could be for pecuniary benefits based on an expectation of price appreciation if demand for the asset grows. It could also be for philosophical reasons, or due to a new utility derived from a unique feature on that blockchain. For example, some assets have been created with properties that promote privacy, and others have been developed to optimize for transaction cost and speed. Nonetheless, the absolute power of asset creators, and subsequently the installed base, diminishes marginally as the network grows. This thesis assumes idealistic cases of decentralization where there is no collusion or opportunity for any central agent to coordinate and implement changes to define otherwise market-determined fundamentals like pricing and supply.

Core blockchain technologies on which most digital assets are developed are open-source, consequently, many digital assets share the same properties and standards. This makes many assets developed over the same blockchain compatible by default. Also, there exists decentralized exchange platforms where multiple digital assets are paired, whether or not they are developed using the same blockchain standard. These assets can be exchanged peer-to-peer based on market-determined prices, making them also compatible for trading purposes, or more appropriately, "cross-fungible" if they have significant market liquidity due to the transparency inherent in their price discovery. This is in contrast with sponsored products where it is more likely for firms with good reputations or large existing networks to favour incompatibility (Katz & Shapiro, 1985).

Digital asset exchanges are generally not promoters of any individual network and they have no incentive to promote the development of one network over another. In fact, their operational model involves facilitating movement between assets, and they thrive on transaction frequency which is conditional upon having at least two assets with a critical mass of users. A market where there is a winner-take-all asset as a result of dominant network effects or otherwise could render them obsolete, as there will be no alternative asset to exchange into. However, centralized exchanges, especially dominant ones, have the power to influence the development of network effects by being selective about which assets to list for trading. An exclusionary model, either for cost, regulatory or other reasons, creates unequal opportunities for assets to amass users. For simplicity I only consider decentralized assets in a theoretical market where they are only exchanged in decentralized marketplaces.

This paper reviews existing management and economics literature alongside data showing the evolution of the cryptocurrency market to further theorize about the dynamics of network effect development for blockchain-based decentralized assets. The underlying question is whether or not a winner-take-all network can be predicted to emerge in decentralized markets where there are no central agents to preserve and appropriate value from such a network, where there are many players due to low barriers to entry, and where multiple competing products are compatible. In the context of blockchain technology, compatibility is considered as the multiple assets sharing one blockchain standard or wallet (storage and governance) system, or where this state is achieved via an adapter (cross-chain technologies). Across blockchains, compatibility can also be described as the pairing of one asset to another such that they can be easily converted into each other.

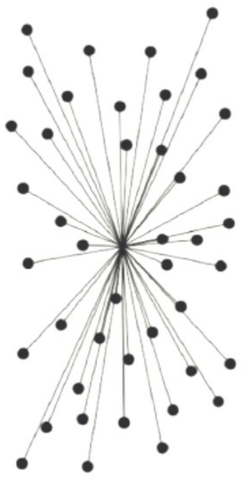
Abstraction Layers of Blockchain Networks

The role of network effects in strengthening market concentration has been well-established. Network effects function to install monopolies (Helias, 2016) and Katz and Shapiro (1985) examined network effects in oligopolistic markets where there is more than one network equilibrium. They expanded network definitions by proposing a broader scope of networks based on compatibility within a market, thereby expanding the scope beyond monopolies to oligopolistic settings. They argue that competing products that are compatible have one network equilibrium, and can therefore be defined as one network. This would imply that different networks of decentralized blockchain assets are indeed a single network on aggregate due to their compatibility. I contend that these networks can both share one equilibrium and multiple equilibria simultaneously depending on the level of network abstraction.

On the one hand, all compatible blockchain assets constitute one network that is incompatible and competing with traditional or sponsored/centralized assets (further study is required to examine the dynamics of network effect development between centralized and decentralized competitors in an oligopolistic setting); on the other hand, within this high-level network are heterogeneous sub-networks that are compatible but in competition with each other. Disallowing for abstraction neglects the heterogeneity of utility between networks (where the assets are not perfect substitutes) and the possibility of multi-homing (where the assets are not complements). The interrelationship between decentralized sub-networks shown in the Diagram 1 below is the scope under review.

Compatible Master Decentralized Network

Centralized Network



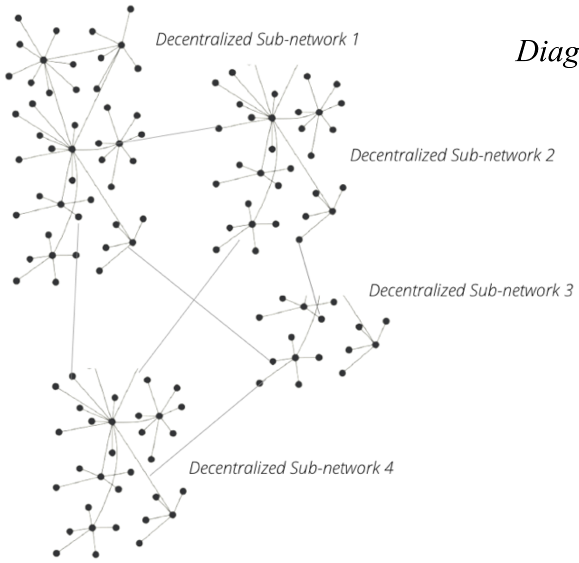


Diagram 1.

Traditional network effects in centralized markets reduce average cost for sponsors (supply-side economies of scale). In both centralized and decentralized networks, they also increase the opportunity cost of switching (demand-side economies of scale). This suggests that as long as strong network effects exist, markets will become concentrated regardless of structure. However, this theory is yet to be definitively established in practice. Weitzel et al. (2000) highlighted common results of previous studies that appear to be in conflict with observable phenomena in modern networks. Examples highlighted include the notions that:

- Demand-sided positive network effects inhibit multiple equilibria and the market will finally lock-in to a monopoly situation with one standard winning total market share.
- In what is called the “start-up problem”, excess inertia can occur as no actor is willing to bear the overproportioned risk of being the first adopter of a standard.
- Laissez-faire of decentralized markets should be replaced by centralized state control to ensure favourable diffusion of technologies subject to network effects.

Weitzel et al. (2000) argued that if optimal networks under (positive) network externalities are monopolies, then all networks are too small. Such a logic applies only in the context of sponsored products where increased network sizes result in falling average costs. In general, their discussion attempts to expose the deficiencies in traditional thinking about network effects, and it proposes a more interdisciplinary theory of network effects where uncertainty, bounded rationality and evolutionary system dynamics on behalf of network actors are incorporated.

By engaging this approach, they propose that the existence of multiple equilibria and the coexistence of optimal network sizes below the population can be better explained. Although their work is in relation to sponsored networks, their proposal to extend network effect theory included that a distinction should be made between centrally and non-centrally coordinated networks.

Decentralized Digital Assets

Following the global financial crisis of 2007 to 2008, an anonymous developer published the white-paper and technology for Bitcoin, the first mainstream decentralized digital asset. The invention was welcomed by the scientific community because it solved a popular "double-spending" problem that has long inhibited the assignment and transfer of value digitally over the internet. The vision behind the creation of the instrument was to develop a self-governed alternative to the traditional centralized financial system with software-defined themes like privacy, transparency, security and neutrality. In the Bitcoin white-paper, Satoshi Nakamoto stated that "what is needed is an electronic payment system based on cryptographic proof instead of trust". The system was structured to rely on independent self-interested actors to run computer nodes which are used to verify transactions and permanently record them on a public ledger. The asset was also programmed to have a capped supply, and supply is created in the form of rewards to network participants that invest computing resources to support the security and on-going functioning of the network.

Since the invention of Bitcoin, thousands of other digital assets have been invented, some with radically unique attributes compared with the Bitcoin blockchain, and others as simply "forks" of the Bitcoin blockchain. A fork is a process whereby all or a subset of node operators collude to create new rules governing transactions, and therefore a new network. New digital assets have been created either as a clone to existing assets, or to improve on specific qualities such as transaction speed, privacy, security, maintenance, etc. Assets can be created for many use-cases, or for no specified one, but the key attribute of a decentralized asset is that its development mechanism is not centrally managed and the underlying technology is auditable. Nonetheless, since its creation, Bitcoin has maintained its position as the dominant network, accounting for about 60% of the market capitalization of all assets. Bitcoin's continued dominance supports the literature on first mover advantages and the formidability of network effects. As the genesis digital assets on the blockchain, it has successfully installed a significant user base with over 50 million wallets without a central sponsor agent.

The strength and growth of this base has added merit to the asset's use case as a payment instrument and the definition of currency as a social construct, a classic demonstration of the network effect phenomenon. Due to the scarcity programmed into the asset, the expansion of the user base has also promoted the asset as a viable store of value. Broadly, most blockchain-based digital assets (also known as cryptocurrencies) compete with Bitcoin for those two use cases in addition to their espoused unique functionalities. This utility as currencies and stores of value have introduced speculation into the asset class, as potential network participants take positions in a network based on their individual cost and utility function. Among other personal variables, this function includes a valuation of the currently installed base, the predicted size of the network and the opportunity cost of participating in the network.

Katz and Shapiro (1985) explained that rational network participants operate with unique cost and utility functions and a diversity of expectations, which could lead to multiple fulfilled expectations of equilibria. A set of network participants may believe that an asset will remain dominant or predict future growth of its user base. This belief will inform their willingness to pay for the asset, and they might decide to concentrate on one asset, or multi-home; that is, maintain a portfolio of different assets. The hybrid and shared functionality inherent in most digital assets ascribe them the attribute of being both substitutable for certain use-cases, and unique for others.

Adoption of Digital Assets

The decision to join a blockchain network or adopt a digital asset is generally influenced by an assessment of the technical conditions, philosophical reasons, network effects and economic incentives. Technical considerations by prospective users could include the appropriateness of the implementation for the suggested use case, and the perceived soundness of the system via expert assessment. Due to the open-source foundations across the industry, several digital assets share technical properties, so the best technical conditions are typically met by new assets. For example, thousands of digital assets are compliant with the ERC-20 token standards on the Ethereum blockchain. The name, ticker, attributes and supply of the asset can be unique, but the underlying technology remains consistent. This creates a system where tools for storage (e.g., hardware wallets) and tracking tools (e.g., Etherscan) can be shared, reinforcing network effects.

Philosophical considerations and agendas can be strong drivers of adoption and stickiness. Bitcoin's growth, and indeed the growth of decentralized digital assets in general, have been driven by participants' belief in individual agency, decentralization, freedom and personal responsibility. Inventions of new blockchain systems and system forks are often executed purely for philosophical reasons. For example, digital assets like 'Monero' were created with significant emphasis on privacy. The Ethereum blockchain standard was developed with the underlying philosophy of universality; that is, without features but as a Turing-complete scripting language for smart contract development. Multiple digital assets can share a global philosophy like decentralization, and individual assets can exist to promote a unique philosophy. The size of a digital asset's community is therefore influenced by the number of users that subscribe to its philosophy.

The value of any blockchain asset increases as the number of users increases. Decentralized digital assets uniquely derive value from network effects. A high and increasing number of network participants suggests that the network is increasingly secure, it positively signals its future prospects for further acceptance and development, and it makes the asset more likely to be liquid and desirable for its practical use cases. A large installed base also confirms a potential participant's bias in favour of the asset and triggers the human instinct to follow the wisdom of the crowd. Network effects generally de-risk an asset for a single individual and increase switching costs for participants.

As many assets have assumed a speculative form, economic incentives have become strong drivers of adoption. Participants pursuing economic incentives may or may not be interested in the technology or the philosophy behind decentralization. Digital assets have been extremely volatile over the past decade, with prices seeing extreme high and low swings. Over any long-term period under review, Bitcoin, for example, have shown strong performance in terms of price appreciation, and this has created a large base of participants that consider digital assets as a viable investment class. New assets are also released to the public via mechanisms like Initial Coin Offerings (ICOs) or Initial Exchange Offerings (IEOs), a small fraction of which has returned significant gains to early participants. Investment considerations are driven by many factors, including the investors' risk profile and strategy, and these all combine to determine how assets are adopted. Also, diversification is a fundamental risk management technique in portfolio construction; this would increase the rate of multi-homing and preserve the market preference for a diverse selection of assets within the category for participants in pursuit of economic incentives.

Fundamentally, the surplus that the investor will derive from purchasing the asset depends on the number of other agents who join the network (Katz & Shapiro, 1985). So, economic considerations are driven by the speculator's expectation of future network size, and also the opportunity cost of investing in another network or asset class subject to the investor's personalized time horizon and returns expectation. Katz & Shapiro (1985) developed a decision flow for the adoption of sponsored assets with network effects. This can similarly be extended to decentralized digital assets as shown below:

Sponsored Networks (Katz & Shapiro, 1985)	**Decentralized Networks**
Consumers form expectations about the size of the network with which each firm is associated.	Consumers evaluate the pre-installed size of the network.
The firm plays an output game, taking consumers expectation as a given, to generate a set of prices.	Prices are determined by the market ex-ante. Consumers form expectations about the future size of the network.
Consumers make their purchase decisions by comparing their reservation price (based on expected network sizes) with the price set by the firm.	Consumers purchase without a reservation price; purchase is based on their expectation of the future size of the network relative to their expectation of the future size of an alternative network.

In summary, the size of any network is a function of the technical conditions, philosophical factors, network effects and economic incentives. A future state where there is an overwhelmingly dominant digital asset implies that one blockchain network simultaneously exhibits superior technical conditions, with enough dynamism to satisfy all possible utilities for blockchain-based digital assets. All participants must be rational enough to ascribe value to this dynamism and superiority, and the asset must embody the diverse philosophies of the population. The asset must already have strong positive network effects such that the switching costs will be prohibitively high, and lastly, the entire population must expect that the asset will indeed be dominant in the future and that it will outperform all other digital assets over any time period. These conditions will be difficult to satisfy to the extent that a winner-take-all digital asset will emerge.

Population Ecology of Decentralized Assets

How do decentralized networks or organizations form, evolve and die? Population ecology theory can be very useful for understanding the evolution of organizations. Prior research on population ecology theory has focused on the perspective of centralized organizations to investigate why and how different organizations exist; however, the theory is perhaps even better adaptable to decentralized populations which better mirror biological ecosystems. According to the work of Hannan and Freeman (1977), competition, natural selection and survival are the main principles of population ecology, and the combination of external factors and inertial pressures in the organization determine the organization's ultimate survival. External pressures that face competing decentralized networks are consistent. These include legitimacy constraints and regulatory barriers to participation in the market. Ultimately, the market, via collective rationality, will evolve to determine the optimal number of viable networks. The networks that represent the best fit to their environment will survive and expand at the expense of others (Hannan and Freeman 1989), and as with biological populations, several species can survive with several interdependent.

The principle of isomorphism is also relevant in answering the question about how many different networks can exist. According to Hawley (1968), "the diversity of organizational forms is isomorphic to the diversity of the environments. In each distinguishable environmental configuration, one finds, in equilibrium, only organizational forms optimally adapted to the demands of the environment". According to DiMaggio and Powell (1983), institutional isomorphism is “a constraining process that forces one unit in a population to resemble other units that face the same set of environmental conditions”. The prediction suggested here for competing decentralized organizations, particularly compatible ones, is that increased interaction will ensure homogenization over time, which will lead to a scale shift, as numerous small organizations fade away to be replaced by a smaller number of larger organizations (Bloodgood, 2011).

Density Dependence Model

The rate of formation and extinction of decentralized networks can also be evaluated via the density dependence model. It brings to the fore the role of competition and legitimacy in determining survival. The model predicts that the rates with which organizations form and die are a function of the number of existing organizations in the population at any given time (Hannan, 1986; Hannan and Carroll, 1992).

Capital is limited, so eventually, new networks will not be able to develop without eroding an existing network. Limited capital could go to the new digital assets, but an increase in failures will signal or trigger resource scarcity within the asset class, which will further discourage new creations (Singh and Lumsden, 1990). The market will experience increasing interaction between network effects of incumbents and start-up problems (liability of newness and smallness) of new entrants. The greater the number of new entrants, the higher the start-up problems and opportunity cost of switching from a viable network (Aldrich & Auster, 1986). “Density has a non-monotonic effect on founding rates; that is, at low density, legitimation increases founding rates, but at high rates of density, competition leads to declining founding rates” (Salimath et al., 2011).

Implications for Market Efficiency

In economic terms, intermediation is a remedy to correct market failure. Information asymmetry therefore allocates market power to central agents, and this creates inherently inefficient markets as centralized agents influence prices, command rents and distort trade (e.g., central and commercial banks in currency markets). The literature suggests that the nature of decentralized networks, following isomorphism across networks and taking into consideration the factors that influence the adoption of digital assets, will be unlikely to create a winner-take-all system. At best, the market will converge into decentralized oligopolistic networks. A research study by Nava (2015) answered the question whether behaviour in decentralized oligopolistic markets can approximate perfect competition.

The study analysed oligopolistic markets in which the role of players in the economy is determined in equilibrium, where the network describes the set of feasible trading relationships and where traders maximize their private utility. The study concluded that when the number of players is small, trade is necessarily inefficient because of the price distortions implied by quantity competition. “The result establishes that trade is almost efficient if and only if it is possible to clear markets without recourse to intermediation in any large community. If so, direct competition among players belonging to neighbouring large communities eliminates resale and restores efficiency” (Nava, 2015). This near-efficiency describes decentralized digital asset networks, but only at scale. In this market, according to Nava’s 2015 model, “all units were sold at one price in any large community; and intermediation persisted only to supply communities of negligible size.” In contrast, centralized agents constrain trade due to their market power, and perfectly competitive resale markets cannot exist. Decentralization supports market efficiency; however, whether or not it optimizes social welfare will be context-dependent.

Current Market Landscape

Several decentralized networks coexist, each operating at significant scale with billions of Dollars in market capitalization and daily trading volume. Each of the networks continuously leverage on their internal network effects to expand, and the strength of an existing network does not prevent newer decentralized network from gaining traction. More so, in some instances, emergent networks can be complimentary to the sustenance of an existing network. For example, a "decentralized finance" (also known as "DeFi") phenomenon has recently emerged along with concepts like "yield farming", where users provide liquidity for certain assets in exchange for rewards in a new cryptocurrency. New networks are then formed out of these reward tokens as value becomes ascribed to them in a public marketplace. A case study of this phenomenon is the Yearn Finance DeFi reward token (YFI) which saw an astronomical rise into the top 50 cryptocurrencies by market capitalization after crossing $1billion in total value within a few weeks of its creation. In this case, the economic incentives for adoption were strong for network development, and while YFI was developed on Ethereum's ERC 20 protocol, making it identical in attributes to Ether (the second largest cryptocurrency by market capitalization) the unique and opportunistic economic incentives for YFI still supported the emergence of a new network at scale without apparently compromising the long-term viability of any existing network.

CONCLUSION

Strong positive network effects increase switching costs, enable market concentration and promote the emergence of monopolistic agents. This can result in a winner-take-all outcome, and sponsors of networks can capture value in a way that is sub-optimal for the overall market. Unsponsored networks like the market for decentralized digital assets are also subject to concentration due to network effects; however, the dynamics of blockchain-based decentralized networks make this outcome unlikely. Competing networks of decentralized digital assets are compatible, making them a single network with one equilibrium at a high level of abstraction when they are considered in aggregate to be in competition with traditional, centralized assets. At a second level of abstraction, multiple networks operate with multiple equilibria, and while network effects apply for each network, several can remain viable. Organizational isomorphism and density dependence can result in newer assets becoming progressively unviable, homogenization can begin and oligopolies of viable networks can emerge over time as a result, but this will only be if the population determines that such an outcome is the best fit for the environment, and not because of market power exertion by a centralized network sponsor. If there are a large number of participants, decentralization, as fundamental to the digital asset ecosystem, ensures near-perfect competition and results in more efficient trading markets. Further study is required to determine the possible impact that proliferation of decentralized networks across more industries will have on governance and social welfare outcomes.

References:

Aldrich, H.E. and Auster, E.R. (1986), "Even dwarfs started small: liabilities of age and size and their strategic implications", Research in Organizational Behavior, Vol. 8, pp. 165-98

Besen, S. M., & Farrell, J. (1994). Choosing How to Compete: Strategies and Tactics in Standardization. Journal of Economic Perspectives, Vol. 8, No. 2, 117-131.

Bloodgood E. (2011). INGO Population Ecology: Isomorphism Among International NGOs? Department of Political Science Concordia University Montreal, QC

Burnham A., Thomas K., Judy F., Mahajan V. (2003). Consumer switching costs: a typology, antecedents, and consequences. J Acad Mark Sci, 31 (2) (2003), pp. 109-126

DiMaggio, P., & Powell, W. (1983). The Iron Cage Revisited: Institutional Isomorphism and Collective Rationality in Organizations Fields. American Sociological Review 48: 147-160.

Farrell, Joseph and Klemperer, Paul (2006). Coordination and Lock-In: Competition with Switching Costs and Network Effects (May). Available at SSRN: https://ssrn.com/abstract=917785 or http://dx.doi.org/10.2139/ssrn.917785

Hannan, M.T. & Freeman, J. (1977). „The population ecology of organizations", American Journal of Sociology, vol. 82, pp. 929– 964.

Hannan, M.T. (1986), Competitive and Institutional Processes of Organizational Ecology, Technical Report 86-13, Department of Sociology, Cornell University, Ithaca, NY.

Hannan, M. T. and Freeman, J., (1989). Organizational Ecology. Cambridge, Mass.: Harvard University Press.

Hannan, M.T. and Carroll, G.R. (1992), Dynamics of Organizational Populations, Oxford University Press, New York, NY

Hawley, A. (1968). Human ecology. In International Encyclopedia of the Social Sciences, ed. D. L. Sills. New York: Macmillan.

Helias, Brattos. (2016). Competition in the presence of Network Effects. 10.13140/RG.2.1.1792.2321.

Katz, M. L., & Shapiro, C. (1985). Network externalities, competition, and compatibility. The American Economic Review, Vol. 75, No. 3, 424-440

Leibbrandt, J.G., (2004). "Payment Systems and Network Effects", Thesis: University of Maastricht, June

Nava, Francesco (2015) Efficiency in decentralized oligopolistic markets. Journal of Economic Theory, 157. pp. 315-348. ISSN 0022-0531

Oren, S. S. & Smith, S. A. (1891). "Critical Mass and Tariff Structure in Electronic Communications Markets," Bell Journal of Economics, Autumn 12, 467-86.

Qiu L., Tang Q., and Whinston A.B. (2015). "Two Formulas for Success in Social Media: Learning and Network Effects", Journal of Management Information Systems, p. 78-108.

Salimath M. & III, Raymond. (2011). Population ecology theory: Implications for sustainability. Management Decision - MANAGE DECISION. 49. 874-910. 10.1108/00251741111143595.

Shankar, Venkatesh & Bayus, B. (2002). Network Effects and Competition: An Analysis of the Home Video Game Industry. Strategic Management Journal. 24. 10.2139/ssrn.296534.

Singh, J. and Lumsden, C. (1990), “Theory and research in organization ecology”, Annual Review of Sociology, Vol. 16, pp. 161-95.

Tucker, C. (2018). Network effects and market power. Antitrust, 32(2), 72–79.

Weitzel, T., Wendt, O., & Westarp, F. v. (2000). Reconsidering network effect theory. Paper presented at the 8th European Conference on Information Systems, Vienna. July

Westarp, F. v., Weitzel, T., Buxmann, P., König, W. (2000): The Standardization Problem in Networks - A General Framework, in: Jakobs, K. (Hrsg.): Standards and Standardization: A Global Perspective, Idea Publishing Group.

CBT

About UCL CBT

The UCL CBT is the first centre globally to actively focus on blockchain-related research on the adoption and integration of Blockchain and Distributed Ledger Technologies into our socio-economic system.

The unique characteristics of the CBT at UCL provides a cross-sectoral platform connecting expertise and drawing knowledge from eight UCL departments centrally in one place. The CBT is a centre of excellence fostering open dialogue between industry players and sharing expertise and resources. It is a neutral think tank providing consultancy services to industry members, dedicated knowledge-transfer activities and cutting-edge in-house solutions.

For engagement outside of the academic world, the CBT's activities have been tailored to industry and policymakers' needs. The UCL CBT draws on its world-leading academic expertise to produce blockchain solutions for industry, start-ups and regulators. With a community of over 180 Research & Industry Associates and Industry Partners, it is the largest Academic Blockchain Centre in the world.

Notable Work

- The CBT released a report on the current adoption of DLT in global physical supply chains. The report featured an analysis of over 100 different projects taking place all over the world in the Grocery, Pharmaceutical and Fashion industries. Access the report here.
- The CBT is leading the Blockchain Technology for Algorithmic Regulation and Compliance (BARAC) project. This is the largest publicly funded blockchain project aimed at the public sector that will be defining feasibility guidelines to policymakers, industry and regulators by identifying problems and associated solutions with a bottom-up approach, built through case studies and proof of concept platforms. For this project, the CBT is partnering with the Financial Conduct Authority and the Singapore Monetary Authority and financial groups and Fintech companies like Banco Santander and R3.
- The CBT is a founding member of the Covid Task Force alongside The International Association for Trusted Blockchain Applications (INATBA) and the European Commission. The task force is convening key players in the global blockchain ecosystem to identify deployable technology solutions that address governmental, social, and commercial challenges caused by COVID. As well as identifying solutions, the Task Force will work to expedite their deployment.
- The CBT successfully funded nine research proposals that investigated topics including stable coin policy, smart contract innovation, blockchain economics and blockchain governance models. Research teams who were funded were made up of individuals from a variety of academic and industry organisations. Learn more about the projects here.
- The CBT launched the Block-Sprint hackathon to promote DLT innovation in the financial services sector. Over 160 individuals took part in the 2019 edition forming teams made up of industry practitioners, academics, and students. Learn about the winners and innovate ideas that were generated in the hackathon here.

About the Discussion Paper Series

The *UCL CBT Discussion Paper is* published on a quarterly basis featuring the latest developments in the blockchain and DLT space. The aim of the discussion paper series is to share recent developments and state-of-the-art solutions on blockchain and DLT of researchers from an interdisciplinary background with the CBT community. All accepted submissions are available in the CBT paper database.

The submissions are circulated among the members of the UCL CBT Editorial Board, led by the Scientific Director so that the results of the research receive prompt and thorough professional scrutiny.

If you are interested in submitting a paper to be included in forthcoming editions, please visit our website here to see what the latest theme and criteria for submission are.

UCL Centre for Blockchain Technologies

http://blockchain.cs.ucl.ac.uk/

UCL Computer Science
Malet Place
London WC1E 6BT
United Kingdom