Does Cryptocurrency Pricing Response to Regulatory Intervention Depend on Underlying Blockchain Architecture?

Andrew Meegan[a], Shaen Corbet[a,b*], Charles Larkin[c,d], Brian Lucey[d,e,f]

[a] *DCU Business School, Dublin City University, Dublin*

[b] *School of Accounting, Finance and Economics, University of Waikato, New Zealand*

[c] *Institute for Policy Research, University of Bath, UK*

[d] *Trinity Business School, Trinity College Dublin, Dublin*

[e] *Institute of Business Research, University of Economics Ho Chi Minh City, Ho Chi Minh City, Vietnam*

[f] *University of Sydney Business School, Sydney, New South Wales, Australia*

[*] *Corresponding Author: shaen.corbet@dcu.ie*

Abstract

Blockchain technology appears to be ready to revolutionise a broad number of industries. However, the blockchain itself contains a number of inefficiencies and areas for improvement, namely: transaction fees and transaction speeds. Directed acyclic graphs (DAGs) address, and improve on these inefficiencies and a number of digital currencies utilising this technology have already begun to appear. This paper provides an explanation of the technology behind DAG-based assets, while identifying and highlighting strategic advantages that DAGs possess over traditional blockchains. We conduct an EGARCH volatility analysis of a range of blockchain-based and DAG-based cryptocurrencies in the aftermath of a range of market shocks, taking the form of regulatory announcements such as bans and broad restrictions for cryptocurrencies. We find that DAG-based assets become increasingly responsive to market shocks as they mature. Such behaviour mirrors that of established cryptocurrencies such as Bitcoin, Ethereum and Litecoin, providing evidence that DAG-based cryptocurrencies now share similar characteristics to traditional blockchain-chain based products.

Keywords: Digital Currencies; Cryptocurrency; Blockchain; Directed Acyclic Graphs; EGARCH.

Preprint submitted to Journal of International Financial Markets, Institutions & Money *May 26, 2021*

1. Introduction

Much research in the area of digital assets and cryptocurrencies has so far been focused almost exclusively on Bitcoin [Nakamoto, 2008]. In addition, any studies surrounding the underlying technology behind these digital assets have been concerned only with blockchain technology. While this focus is understandable, given the prominence of blockchain-based cryptocurrencies and the fact that the largest asset (Bitcoin) utilises this technology, there is a need to introduce alternative (and perhaps more efficient) consensus methods into the conversation. Studies such as Iwamura et al. [2014] have previously suggested that Bitcoin will eventually be overtaken by an improved, more efficient, cryptocurrency. Once such area for improvement is the underlying 'consensus' method. Indeed, blockchain technology itself contains a number of areas which could be improved on by alternative technological methods. Once such method is the use of directed acyclic graphs (DAGs henceforth) in substitution for blockchains. DAG-based assets use a different method to achieve consensus between network participants and this consensus method allows for the elimination of transaction fees while simultaneously providing an increased ability to scale. Both are problems which have thus far plagued blockchain assets[1]. The continuing increase in Bitcoin transaction fees, combined with large delays in confirmation times, have rendered Bitcoin virtually useless as a payment method for day-to-day transactions. In many cases, the cost of the transaction fee would surpass the value of the transaction itself. As such, DAG technology has already been employed in the creation of a number of prominent digital assets, which are appropriate for use with micro-transactions, namely: IOTA, NANO and Obyte[2].

IOTA claims to address the scalability issues posed by blockchain. It is found to be quantum-

[1] As Bitcoin and Ethereum have grown, the networks have repeatedly been brought to a standstill, as blocksizes struggle to accommodate the increasing number of transactions. On the Bitcoin network, only a set number of transactions can be included in each block (with each new block being added every 10 minutes) and space is at a premium. As such, network participants vie to have their transactions included ahead of others. Miners on the Bitcoin network can themselves choose which transaction to include in each block. To conduct a transaction on the Bitcoin network, each user includes a fee - an incentive for the miner to include their transaction in a block. This fee is not fixed however and can be determined individually by each user. As such, with space at a premium, the primary manner for a user to ensure their own transaction is processed ahead of others is to increase the transaction fee on offer to the miners. This process has led to a consistent increase in the fee that must be paid for a transaction to be included in a block by miners and confirmed. A number of attempt have been made on the Bitcoin network to solve this issue. Protocol updates such as SegWit (segregated witness) have been proposed and implemented, but in many cases, debates over these updates have caused a considerable amount of friction within the Bitcoin community.

[2] On 17 January 2019, Obyte was formed after a re-branding of the cryptocurrency Obyte. The decision was made in an announcement stating: 'Our new name is short, catchy, easy to pronounce, easy to spell and meaningful. Simplicity is beauty.'

resistant and, perhaps most importantly, operates without any transaction fees. The existence of transaction fees on the blockchain is both a necessity, which incentivises miners to continue securing the network, and also an impediment which prevents blockchain technology from being used for micro-transactions. Such micro-transactions would be an inherent requirement in any future communication between IOT (internet of things) devices. IOTA overcomes this problem, through the use of directed acyclic graphs (DAG) and a new data-structure known as 'The Tangle' [Popov, 2016]. In order to make a transaction themselves, each user is required to validate two previous transactions. In turn, subsequent transactions will then validate the user's transaction. In this manner, miners are no longer necessary to validate transactions and maintain the network. Additionally, transaction fees are no longer necessary, as network participants are required to secure the network in order to enable their own transaction, removing the need for any other financial incentive. In addition to removing the need for transaction fees, the tangle also operates without the need for intensive proof of work calculations, preventing the wastage of large amounts of energy and computing power.

NANO employs DAG technology in a consensus method known as a 'Block-Lattice'. The goal of NANO is similar to that of IOTA in that it aims to facilitate the use of digital currencies in everyday transactions. Rather than require users to maintain a global ledger, NANO simply requires each user to maintain a record of their own transaction history and current balance. In this manner, each individual chain can update asynchronously to the rest of the block lattice (the combination of all individual chains on the network) and transaction speeds are greatly reduced. The consensus method used within Obyte is based on the establishment of a total order (or 'Main-Chain') within a DAG. New transactions are linked to older ones, and a central chain is formed within the DAG. This main-chain is chosen so that all transactions within the DAG can be related back to it. The main-chain itself is then verified by a number of user-selected nodes known as 'witnesses'.

Our research provides the first examination of the consensus methods behind these three digital assets, and the underlying DAG technology itself. Through an EGARCH-analysis of the volatility of the prices of these cryptocurrency assets, we note a number of distinct differences between DAG and blockchain technology, namely, the removal of the need for resource-intensive mining and partition tolerance. Partition tolerance refers to the ability of the network to continue functioning, even if a portion of that network is disconnected. The ability for devices to temporarily disconnect from the network increases the potential use cases for assets built on such technology. The emergence of

IOT devices will continue in the future, and while blockchain based assets do not lend themselves well for use in a machine economy, we note the potential for DAG-based assets to be used in the area of machine-to-machine payments, as well as in other areas such as fog computing. We identify, and discuss, a number of key strategic advantages that DAG-based assets hold over blockchain, these include: an increased ability to scale; an absence of transaction fees; a new set of economic incentives; and a resistance to quantum computing (a long-term threat to all blockchain based digital currencies).

In an attempt to observe the market behaviour of these alternative forms of digital currencies, and indeed compare them with more traditional assets such as Bitcoin, Ethereum and Litecoin, we examine the volatility characteristics of a group of DAG-based assets Using a EGARCH methodology, we examine the reaction of a number of blockchain and DAG-based assets to regulatory shocks in the market. Using a sample of nine digital currencies, we construct three groups (a group of large-cap blockchain based assets, medium-cap blockchain based assets, and a group of DAG-based assets). We identify thirteen key regulatory announcements that took place between January 2017 and December 2019. These announcements include the banning of all ICOs[3] by the PBOC (People's Bank of China) in September 2017, the SEC's (U.S. Securities and Exchange Commission) crackdown on ICOs in December 2017, and the intention of the South Korean government to regulate, rather than ban, cryptocurrency trading in January 2018. We examine the EGARCH volatility reactions of each of the nine assets to each of the individual thirteen announcements, as well as the reaction to the group of thirteen announcements as a whole.

We uncover a number of differing reactions between large-cap blockchain assets and DAG-based assets. We note that, as IOTA has matured, it has displayed a significant exposure to individual regulatory events that was not observed in the cases of Bitcoin, Ethereum, and Litecoin. Despite this, neither NANO nor IOTA display evidence of significant volatility changes over the full sample of announcements. This is in contrast with the three large-cap assets, which all displayed a significant reduction in volatility over the full sample. These results suggest that, while initially remaining immune to the market forces that affected the larger blockchain assets, as DAG assets such as IOTA

[3]An Initial Coin Offering (or ICO, borrowing the language of the Initial Public Offering (IPO) used in equity markets) is used by startups to bypass the rigorous and regulated capital-raising process required by venture capitalists or banks. In an ICO campaign, a percentage of the cryptocurrency is sold to early backers of the project in exchange for legal tender or other cryptocurrencies, but usually for Bitcoin.

and NANO have matured they have begun to show an increased sensitivity to these same forces. In other words, they have begun to display the same reactions as those of Bitcoin, Ethereum, and Litecoin, the prominent blockchain based currencies. Any concerns therefore that, while effectively improving on blockchain technology, DAG-based assets would produce a differing response and fare worse in the market, seem unfounded.

The remainder of this paper is organised as follows: Section 2 presents a review of previous literature on the subject and an explanation of blockchain technology. Section 3 explains the technology behind directed acyclic graphs and the tangle consensus method, as well as highlighting a number of technological features unique to these methods. It further details other implementations of DAG technology, namely the digital currencies NANO and Obyte. Section 4 presents our EGARCH methodology and Section 5 presents our empirical results. Section 6 highlights a number of areas in which this new technology could be valuable, as well as identifying key strategic advantages that DAGs possess over blockchains. Section 7 concludes.

2. Previous Literature

Dwyer [2015] explains the equilibrium that Bitcoin, and other similar digital currencies, derive their value from. He highlights the potential changes that will arise once mining is no longer required (the full supply of Bitcoin has been issued). He notes that transaction fees will become a more important factor in creating an equilibrium, once there are no longer any mining rewards. The author also examines the rise of online exchanges and the potential for Bitcoin to undermine a government's ability to generate revenue from substantial inflation.

Marimon et al. [2012] note that, for an equilibrium with positive values for private currencies to exist, there must be a reputational equilibrium in which the private currencies are distinguishable. This possibility of the distinguishing factor being a physical characteristic is redundant when dealing with digital currencies. As such, there must still be a factor which prevents the currencies from being perfect substitutes for each other. In the case of digital currencies, characteristics such as block sizes, hashing algorithms, supply restrictions, and underlying protocols are all distinguishing factors. In the case of coins such as Bitcoin and IOTA, the distinguishing factor is the underlying technology and consensus method behind both coins. Bitcoin relies on a blockchain protocol while IOTA relies on a directed acyclic graph (DAG) protocol, known as 'the tangle'.

A blockchain consists of a database of transactions, known as a ledger. This ledger is distributed among all participants in the network, unlike traditional ledgers which are maintained by one central organisation (usually a bank). Members of the network maintain the ledger and add to it at fixed intervals (blocks). The addition of blocks is both the method by which new data is added to the ledger and the way in which it is secured. In most scenarios a block will consist of a number of transactions which have taken place since the last block was added (unless there were more transactions than available space in the block, in which case there will be some transactions left over that will need to be added to future blocks), as well as a header. The header contains various information including the hash of the previous block, the merkle root, and the nonce[4]. To add this new block to the chain, miners must hash the block's header repeatedly using a variety of different nonces. The nonce is incremented repeatedly until the result of the hash is under the current target of the block. In reality, this process is time and resource intensive, and will require miners to compete with each other to find the correct nonce. Miners are rewarded for allocating their resources to this process by receiving a block reward (in the case of Bitcoin, a payment of coins that decreases over time) if they are first to find the correct nonce. Once the correct nonce has been found, the block is successfully added to the chain and the process starts again. The hash of this block is then included in the next, linking these blocks together. This process ensures that, once a block has been added to the chain, it becomes virtually impossible to alter the information contained in earlier blocks. Because each block contains a hash of the previous block, any change to said blocks (no matter how small) will change the hash. Because this hash is contained within all future blocks (and will in turn change their hashes) it will create a different chain. A different chain such as this is referred to as a fork. Miners ultimately decide which fork they will add blocks to, but it will typically be the largest chain. As such, any attempt to change data will result in a fork, and that chain will eventually cease to be added to, all while the original chain continues to be maintained and added to. Any rogue forks will simply be disregarded by the network participants when deciding the state of the ledger. A thorough explanation of blockchain technology is contained within Dwyer [2017]. No such papers regarding DAG technology currently exist, and we provide a

[4] In cryptography, a nonce is a random number used for authentication. In the Bitcoin protocol, the nonce is a 32-bit field whose value is set so that the hash of the block will contain a specific number of zeros. It is impossible to predict which random number will result in the correct hash. As a result, a number of different nonces values must be tried until the hash containing the correct number of zeros is found.

detailed explanation in this paper.

Corbet et al. [2019] provide a detailed overview of cryptocurrencies as a financial asset through the implementation of a systematic analysis. Much of the research on cryptocurrencies to date has focused on the diversification benefits and the efficiency of price and positioning as a financial product. Using spanning tests, Brière et al. [2015] found that Bitcoin investments offer significant diversification benefits. The inclusion of even a small proportion of Bitcoins may dramatically improve the risk-return trade-off of well diversified portfolios. The authors however state that the results should be taken with caution as the data may reflect early stage behaviour which may not last in the medium or long-run. Corbet et al. [2018] analysed both in time and frequency domains, the relationships between the three most popular cryptocurrencies and a variety of other financial assets to find evidence of the relative isolation of these assets from the financial and economic assets. Results show that cryptocurrencies may offer diversification benefits for investors with short-term investment horizons. Baur et al. [2017] analysed the statistical properties of Bitcoin to find that it is uncorrelated with traditional asset classes in periods of financial turmoil. Transaction data of Bitcoin accounts show that Bitcoins are mainly used as a speculative investment and not as an alternative currency or medium of exchange. Dyhrberg [2016a] exported the financial asset capabilities of Bitcoin using GARCH methodologies, showing several similarities to gold and the dollar, indicative of hedging capabilities and advantages as a medium of exchange. Bitcoin is found to have a place on financial markets and can be classified as something between gold and the US dollar, on a scale from pure medium of exchange advantages to pure store of value advantages. Baur et al. [2017] extended the work of Dyhrberg [2016a] to replicate the above findings and demonstrates that exact replication is not possible. Instead, alternative statistical methodologies provide more reliable, however, very different returns. The findings show that Bitcoin exhibits distinctively different return, volatility and correlation characteristics compared to other assets including gold and the United States dollar. Dyhrberg [2016b] showed that Bitcoin can be used as a hedge against stocks in the Financial Times Stock Exchange Index and against the US dollar in the short-term. Bitcoin is thereby found to possess some of the same hedging abilities as gold and can be included in the variety of tools available to market analysts to hedge market-specific risk.

Market efficiency can be determined by a number of specific factors, however, the market efficiency of cryptocurrencies can be measured through a host of progressive factors including the existence of a new futures exchange, liquid cross-currency indices and the relative reduction of intraday volatility although daily volatility remains high. While investigating the general behavioural aspects of cryptocurrencies such as Akyildirim, Corbet, Lucey, Sensoy, and Yarovaya [Akyildirim et al.], Corbet et al. [2018], Katsiampa et al. [2019] and Akhtaruzzaman et al. [2019], Corbet et al. [2020a] examined the reaction of a broad set of digital assets to US Federal Fund interest rates and quantitative easing announcements. They find a broad range of differing volatility responses and feedback, dependent on the type of cryptocurrency investigated and whether the cryptocurrency was mineable or not (as discussed in Corbet and Katsiampa [2018], Corbet et al. [2019], Katsiampa et al. [2019]). Antonakakis et al. [2019] employed a TVP-FAVAR connectedness approach in order to investigate the transmission mechanism of contagion in the cryptocurrency market to find that dynamic total connectedness and large dynamic variability ranging between 25% and 75%. Further, periods of high market uncertainty correspond to strong connectedness. Walther et al. [2019] used a GARCH-MIDAS framework to forecast the daily, weekly, and monthly volatility of five highly capitalised cryptocurrencies to show that the Global Real Economic Activity provides superior volatility predictions for both, bull and bear markets. Corbet et al. [2018] found evidence of the relative isolation of Bitcoin, Ripple and Litecoin and a broad variety of other financial assets. Corbet et al. [2018], while utilising the bubble identification methodology of Phillips et al. [2011], found clear evidence of periods in which Bitcoin and Ethereum were experiencing bubble phases. Corbet et al. [2020b] examine the relationship between news coverage and Bitcoin returns, extending the approach developed by Birz and Lott [2011] to examine the hypothesis that Bitcoin returns are similarly affected by macroeconomic news announcements. By controlling for a number of potential biases the author's determine that news relating to unemployment and durable goods announcements are found to be significantly linked to Bitcoin returns. Further, Corbet et al. [2020] investigated the situation surrounding the price appreciation of Kodak in the aftermath of their announcement of KODAKCoin, representing their ambitious attempt to enter the cryptocurrency market despite their expertise primarily surrounding photography products.

In Hayes [2017] a regression model was estimated which points to three main drivers of cryptocurrency value: the level of competition in the network of producers, the rate of unit production, and the difficulty of algorithm used to 'mine' for the cryptocurrency. The author establishes a no-arbitrage situation for Bitcoin-like cryptocurrencies followed by the formalisation of a cost of production model to determine the fair value of a bitcoin. Tiwari et al. [2018] investigate the informational efficiency of Bitcoin using a battery of computationally efficient long-range dependence estimators for a period spanning over July 18, 2010 to June 16, 2017. The authors find that the market is informational efficient, consistent with the recent findings of Nadarajah and Chu [2017]. Feld et al. [2014] present novel insights into Bitcoin's peer-to-peer (P2P) network with a special focus on its distribution among distinct autonomous systems. Their findings lead to conclusions about the resilience of the Bitcoin ecosystem, the unambiguous nature of the blockchain in use, and the propagation and verification of transaction blocks. Brandvold et al. [2015] found that Mt.Gox exchange was the market leader with the highest information share, which was found to be dynamic and evolve significantly over time. Brauneis and Mestel [2018] extended existing literature by performing various tests on the efficiency of several cryptocurrencies. Additionally, they link efficiency to measures of liquidity and find an increase in inefficiency as liquidity increases.

3. The technology behind DAGs and The Tangle

3.1. Directed Acyclic Graph (DAG) and The Tangle

A directed acyclic graph (DAG) is characterised by a set of relationships that are unidirectional, and results in a series of one-way transactions. A DAG consists of a series of vertices and edges. The vertices are sequenced such that all edges travel in the same direction from the beginning of the sequence to the end. Edges are directed from one vertex to another, in such a manner that it becomes impossible for a vertex to loop back upon itself again. This method enables transactions to be verified, without the possibility of a new transaction looping back and verifying previous transactions in the chain. The DAG method ensures that, once a transaction has been verified a sufficient number of times, it becomes effectively impossible to remove or alter that transaction due to its position in the entire chain.

The primary implementation of a DAG in digital currencies is in the data structure used by the currency IOTA, known as 'The Tangle'. The tangle removes transaction fees by creating a new incentive for network participants. In order to perform a new transaction, a user must validate two existing transactions. Having done this, the user's new transaction will subsequently be verified by another network participant. By requiring a user to verify two existing transactions each time they attempt to issue their own transaction, the network remains secure without the need for miners to verify each individual block of transactions. As each transaction is verified by two subsequent transactions - which in turn are verified by a combination of four transactions (two for each), a transaction becomes intrinsically linked within the entire chain, or tangle, once it has been verified. This produces the same end result obtained by the blockchain (irreversible transactions), without the need for nodes to verify and download the entire blockchain.

For security purposes, a coordinator is currently required to oversee all transactions that take place on the network, until the network can sustain itself from malicious attacks. Once the coordinator is removed, approval of transactions will operate using a random-walk Monte Carlo method. A random integral algorithm will jump to random transactions and approve them. Economic incentives, in the form of transaction fees, are no longer necessary to determine the order in which transactions will be processed. In this manner, The Tangle can select which transaction a user will be verifying, when the attempt to issue their own transaction, without the need for a coordinator or fees.

3.2. The mining process

Consensus within the blockchain refers to the manner in which validators (or nodes) agree upon which version of the blockchain to continue using. Within the blockchain, consensus is agreed upon by selecting the fastest growing fork of the blockchain, i.e the one with most computing power attached (most users). Consensus within the tangle operates in a different manner through the use of weights. Each transaction is assigned a weight, dependent upon the number of times it has been directly, and indirectly, verified. If a transaction does not gain a sufficient number of verifications, and its weight remains low, it will become isolated from the rest of The Tangle, while the entire chain continues to grow.

Transaction fees play a role in the selection, by miners, of which transactions to include in each block (and the preference each is given). The absence of such fees in The Tangle means that selection order is dictated through the use of a random walk Markov chain. In a similar manner to the blockchain, transactions are not accepted until they have received a sufficient number of references (both direct and indirect). Due to the absence of competition among miners (as a result of the removal of block rewards and the shared incentive among all users), the mining algorithms used within The Tangle are not required to be as intensive as those of Bitcoin or Ethereum. The reduction in required computing power will allow IOT (Internet of Things) devices to complete the proof of work required to verify transactions, using inbuilt ASIC chips.

3.3. Technological Features

3.3.1. CAP (Consistency, Availability, Partition Tolerance) Theorem

Distributed data stores such as the blockchain and the tangle are all subject to Brewers CAP (consistency, availability, partition tolerance) theorem. Consistency can be described as ensuring that all databases contain the same data. Availability refers to the availability to query this database. Partition tolerance refers to the ability of the system to continue functioning, despite a portion of the network no longer being connected. Brewers theorem states that it is impossible for a distributed system to simultaneously provide more than two out of these three. The blockchain enforces a consistent global state to guarantee consistency across the entire database (the ledger) and is available to query at any time, through the use of an explorer. However, this means it must sacrifice partition intolerance. If a portion of the network becomes disconnected, yet continues to verify transactions, this will eventually result in a fork in the ledger in which the disconnected portion is no longer consistent with the rest of the ledger and becomes incompatible. IOTA, and The Tangle, favour the combination of partition tolerance and availability, with the expectation that consistency will occur subsequently. Such a combination makes the IOTA network more flexible, a characteristic which is essential to IOT and IOT devices. As previously stated, the tangle is partition tolerant, meaning that clusters off the network can disconnect, continue to interact and verify transactions, and then, once reconnected to the internet, the cluster will be re-absorbed naturally into the tangle. Blockchains are required to transmit large amounts of data across the internet, despite the fact that it, and the required bandwidth, are scarce, expensive resources. Rather than transfer large amounts of data over these scarce resources, IOT devices can utilise mesh networks[5] to reduce costs associated with bandwidth usage and battery life. As such, an IOT device may only relay data over the internet, to the full network, once or twice a day. While this allows an IOT device to solves the internet usage problem, in the case of the blockchain, this method would lead to the creation of a fork. The partition created by the above method, would mean that the fork was no longer compatible with the main-chain. This resulting fork would require a considerable amount of effort in order to make it compatible again, ensuring it could be recombined and synced with the

[5]Mesh networks consist of a number of nodes which are connected to each other, to enable the efficient transfer of data. In an IOT economy, mesh networks are attractive as they provide an inexpensive way to connect devices to each other. The mesh network allows devices to wirelessly connect to each other, without the need for a central hub or internet service provider.

main chain again. Tangle transactions can be queried in a similar manner to the blockchain, via explorers. Through these explorers, consistency also occurs, overcoming the CAP problem.

3.3.2. Security

Bitcoin hashing is driven to the extreme because of the economic incentive (mining reward) required to operate the network. As a result of this, and the competition it creates on the network, ASIC complexity continually increases, leading to a corresponding increase in power usage. IOTA, and the Tangle network, is resistant to ASIC attackers. The cost to an individual, of assembling enough ASIC chips to attack network, would not be economically viable, as the attacker would be required to assemble more computing power than the combination of billions of legitimate IOT devices. Thus, attacking the Tangle network provides no economic incentive to the potential attacker. A scenario may arise, however unlikely, in which an individual with the required resources possessed no economic incentives for attacking the network. In this scenario, the attacker would still be required to connect to each of the individual nodes due to the presence of manual tethering, as opposed to automatic peer discovery, making such an attack even more implausible. Finally, if such obstacles were overcome, the attacker would only be able to intercept a minute number of transactions. Furthermore, the Tangle is structured in such a manner so that additional hashing power serves to strengthen the network itself. As a result of this, an attacker would be required to continually assemble larger and larger amounts of hashing power, after each attack. This structure renders such forms of attack virtually useless. the Tangle is structured in such a manner, so that the entire network can never be fully attacked, only a small partition, due to the fact that the network is never in a continuous global state (as previously explored in relation to the CAP Theorem).

3.4. Other practical implementations of DAG technology

As well as IOTA, and the Tangle application, two other notable assets have been built using the DAG method. Both these coins, NANO and Obyte, use DAGs in favour of blockchains, however the specifics of each vary significantly.

3.4.1. NANO and The Block-Lattice

NANO (formerly RaiBlocks) was first proposed in 2014 and implements DAG technology in the form of a block lattice. In a similar manner to IOTA, the goal of this technology is to provide a practical cryptocurrency that can facilitate everyday transactions. NANO uses balance-weighted voting to achieve consensus. Each account has it's own blockchain, which can only be updated by it's owner. This account blockchain records the transaction history, and the current balance, of that individual account. In this manner, each chain updates asynchronously to the rest of the block lattice, increasing the speed of transactions. Transferring funds from one account to another requires to transactions. A send transaction deducts the relevant amount from the sender's balance, and a receive transaction credits the relevant account with the correct amount. In this manner, a transaction need only be verified by the two parties involved. By separating the transfer into two transactions, incoming transfers are sequenced, transaction sizes are reduced, the total data that must be stored on the ledger is reduced (and allows for 'pruning' of the ledger) and settled transactions can be distinguished from unsettled ones. Despite the increase in transaction speed, there will still be a delay window when validating transactions (due to the identifying and handling of malicious players on the network). Transactions are therefore separated into two types: Settled and Unsettled. Unsettled transactions are ones which have not yet been incorporated into the receiver's cumulative balance. Transactions in which the the account has successful generated receive blocks are known as Settled. This method replaces the confirmation methods used by alternative cryptocurrencies.

A case of multiple accounts transferring to the same receiving account is an asynchronous operation, the network needs to determine which transaction took place first. A blockchain solves this problem by requiring all users to maintain a full copy of the global ledger (the correct state is deemed to be the chain with the largest number of nodes), however NANO only requires each user to maintain a record of their transactions and balance. As such, in the case of multiple transactions, the receiving account decides themselves which one arrived first, and expresses this through the signed order of incoming blocks. Each transaction is encoded with the accumulated balance of the account in question. As such, nodes which don't want to expend power maintaining a full record of transactions, need only store the latest block, as it contains all the relevant information (the current balance). In doing so, they can discard historical data ('pruning') and still correctly reflect the current state of the account.

3.4.2. Obyte and Main-Chains

Obyte was launched in December 2016 and, unlike IOTA, contains transaction fees and a slight delay on confirmations. Obyte implements DAG technology in the form of a main-chain. This consensus method is based upon establishing a total order within the DAG. New transactions are linked to older ones, so that a single-chain is formed within the DAG. All transactions can be related back to this central chain. This central chain is known as the main-chain, and all transactions will either lie directly on the chain, or be reachable in a relatively small number of jumps along the edges of the graph. The main chain is determined using an algorithm that selects the best fit, based on all available data (in a similar method to fitting a line of best fit in OLS regression). To prevent double spending, indices are assigned to each of the units in the DAG. The genesis unit itself has an index of zero, the next main-chain unit that is directly related to the genesis unit is given an index of one. This process is repeated as indices are assigned to all units along the main-chain. If a unit does not lie on the main-chain, then the first main-chain index in which the unit is mentioned is used. Should two units conflict (a double-spend attempt) the unit with the lowest index will be considered valid (because it is deemed to have taken place first). Should both indices be the same, the hash value is used to determine which is valid. Unlike blockchain, in which only the largest chain is deemed to be valid, both conflicting units ultimately remain in the DAG, both the validated and rejected unit.

The main-chain is verified by a number of user-trusted nodes known as 'witnesses'. As with alternative coins, these witnesses effectively vote on the correct state of the DAG, and are used to secure the network. Witnesses may be reputable individuals or organisations (anyone with an interest in maintaining the network's security). Main-chain candidates are measured by counting the number of witness-authorised units that appear along that chain, until the majority has been reached. At this stage, the longest path between that point and the genesis unit is measured. This length is referred to as the level. Whichever candidate chain has the largest level is selected as the valid main-chain. This method prevents potential attackers from creating a chain of invalid units, and then attempting to re-join them into the main-chain. As long as these units have not been verified by any witnesses, they will not have enough witnessed units. Once the chain re-joins the main-chain, the double-spend unit will be deemed invalid, because the valid counterpart will have the lower main-chain index.

This system relies on trusting witnesses to only validate units on legitimate chains. Ultimately, the users of the network elect the witnesses, and can choose to remove them at any time, should they become unhappy with their behaviour. Each unit must list 12 witnesses. This number prevents against the potential failure of some of those witnesses, and ensures that the user can change their list of witnesses if they desire to. Should a user believe a witness has lost credibility, they can replace that user in their list. While this allows them to remove any rogue witnesses, their witness list may only differ from that of other units by one position. This prevents drastic changes and ensures that a general consensus must be met for large changes (more than one position).

4. Data and Methodology

We construct our dataset by selecting nine digital currencies and dividing them into three groups. The daily closing prices of each of these assets are presented in Figures 1, 2 and 3. Group 1 contains three large capitalisation assets which are constructed on blockchains. The three assets, Bitcoin, Ethereum and Litecoin, are respectively ranked 1st, 2nd and 5th in terms of total capitalisation in the digital currencies market. Group 2 contains three medium capitalisation assets which are also constructed on blockchains. These three assets, Verge, Qtum and Factom, are respectively ranked 27th, 20th and 75th in terms of total market capitalisation. Group 3 consists of the three most prominent cryptocurrencies which are built upon a directed acyclic graph, IOTA, NANO and Obyte. These three assets are respectively ranked based on their total market capitalisation as of December 2019. We source daily returns data for each of these three assets and use closing prices to construct the daily percentage change in price for each of the nine assets. Our sample period extends from 1 January 2017 to 31 December 2019. Associated summary statistics for both the price levels and volatility of our selected cryptocurrency are presented in Table 2. Daily percentage changes in the prices of the nine assets in our sample are presented in Figures 4, 5 and 6. We construct a cryptocurrency index which is used to represent the general movement of the market. We also source returns data for three market indices, the Dow Jones, EuroStoxx and Nikkei.

Insert Figures 1 through 6 about here

We construct a database of regulatory announcements with emphasis on early announcements during 2017 and 2018 during the rapid price appreciation of Bitcoin. It was during this time that much regulatory concern surrounded the potential bubble-like behaviour of cryptocurrencies and the inherent potential for fraudulent behaviour that was contained within (as discussed in Akyildirim et al. [2019], Corbet et al. [2018, 2020,a]). We consider any announcement that was made by an official government agency, regarding the regulation of digital currencies. Seventeen announcements are identified between January 2017 and December 2019. Due to the close proximity of some of these announcements, we ultimately choose to include 13 in our database. These thirteen announcements span four countries and are listed in Table 1. We construct thirteen dummy variables, one for each of the announcements. Dates that fall in the thirty-day period following the announcement take the value of one, all other dates in the sample take the value of zero. We further construct an 'all events' variable in which any date in the thirty-day period following an announcement takes a value of one, all other dates take a value of zero.

Insert Tables 1 and 2 about here

To begin our analysis, we first utilise a multivariate EGARCH(p,q) methodology to identify scale of the change in volatility in the period after the each identified regulatory event. At this stage, a number of goodness-of-fit testing procedures identified the EGARCH(1,1) model as the best selected to identify specific volatility changes in cryptocurrency returns, thus we exercise our analysis using this model.[6] The EGARCH specification developed on that of the GARCH specification proposed by Bollerslev [1986] and was designed to include lagged conditional variance terms as autoregressive terms. We specifically develop on an EGARCH methodology to analyse the volatility effects within the aviation industry due to aviation disasters. We first let $r_t = [r_{1,t}, ..., r_{n,t}]'$ be the vector of financial time series returns and $\varepsilon_t = [\varepsilon_{1,t}, ..., \varepsilon_{n,t}]'$ be the vector of return residuals obtained after some filtration. Let $h_{i,t}$ be the corresponding conditional volatilities obtained from a univariate EGARCH process. We assume that $E_{t-1}[\varepsilon_t] = 0$ and $E_{t-1}[\varepsilon_t \varepsilon_t'] = H_t$, where $E_t[\cdot]$ is the conditional expectation on $\varepsilon_t, \varepsilon_{t-1}, ...$ Then the asset conditional covariance matrix H_t can be written as

$$H_t = D_t^{1/2} R_t D_t^{1/2} \tag{1}$$

where $R_t = [\rho_{ij,t}]$ is the asset conditional correlation matrix and the diagonal matrix of the asset conditional variances is given by $D_t = diag(h_{1,t}, ..., h_{n,t})$. We express the variance equation of our EGARCH model as follows:

[6] EGARCH exploits information contained in realised measures of volatility while providing a flexible leverage function that accounts for return-volatility dependence. While remaining in a GARCH-like modelling framework and estimation convenience, the model allows independent return and volatility shock and this dual shock nature leaves a room for the establishment of a variance risk premium.

$$R_t = a + b\prime X_t + \varepsilon_t, \text{ where } \varepsilon_t|\Omega_t \sim iidN(0, h_t) \tag{2}$$

$$\ln(h_t^2) = \omega + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) + \beta\ln(h_{t-1}^2) + D_t \tag{3}$$

which states that the value of the variance scaling parameter h_t now depends both on the past value of the shocks, which are captured by the lagged square residual terms, and on past values of itself, which are captured by the lagged h_t terms. Specification tests found that the EGARCH(1,1) model served as the best fitting to estimate volatility effects through the use of dummy variables that are used to denote both the time-of-the-day and also periods of substantial traditional market volatility.[7] It is also necessary to mitigate international effects which can be completed through the inclusion of the returns of traditional financial indices in the mean equation of the EGARCH(1,1) methodology. After a number of attempted variants, the S&P500 was selected as the most suitable exchange to incorporate international effects[8]. The volatility sourced in shocks that are incorporated in the returns of traditional financial markets are therefore considered in the volatility estimation of the selected structure. In summary, the estimated model has the following form:

$$R_t = a_0 + \sum_{j=1}^{n} b_j R_{t-n} + b_2 S\&P500_t + \varepsilon_t + D_t \tag{4}$$

$$\ln(h_t^2) = \omega + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) + \beta\ln(h_{t-1}^2) + D_t \tag{5}$$

where $R_{i,t}$ represents the return on asset i at time t and R_{t-1} represents the first lag of returns r_t. $b_2 S\&P500_t$ represents the return on the S&P500 index and it included as a proxy for market effects. Finally, D_t is included in the variance equation to provide a coefficient relating to the

[7]The optimal model is chosen according to three information criteria, namely the Akaike (AIC), Bayesian (BIC) and Hannan-Quinn(HQ), all of which consider both how good the fitting of the model is and the number of parameters in the model, rewarding a better fitting and penalising an increased number of parameters for given data sets. The selected model is the one with the minimum criteria values. We also used a variety of dummy-lengths, denoted as D_t in the variance equation, but the thirty-day period after each selected event was denoted as the most stable specification across our selected methodologies. Results of all these specification tests are available from the authors on request.

[8]A number of alternative methodological structures and representative measures of international effects were considered. For brevity, results relating to these analyses are available from the authors on request.

volatility response to the thirty-day period after each identified event. Bollerslev [1986] showed that restrictions on the parameters for positivity, $\omega > 0$, $\alpha \geq 0$ and $\beta \geq 0$, and the wide-sense stationarity condition, $\alpha + \beta < 1$. Bollerslev [1986] also proved that if the fourth order moment exists, then the model can handle leptokurtosis.

5. Empirical Results

Table 3 displays the volatility effect of regulatory announcements on Bitcoin returns. The coefficient D_t represents the change in volatility, based on our previously outlined EGARCH methodology. An EGARCH model is run using an indicator variable to represent each of the thirteen individual events as presented in Table 1, as well as a variable combining all thirteen event windows (denoted as 'All Events').

Insert Tables 3, 4 and 5 about here

Bitcoin experiences a significant reduction in volatility during events 5, 10, 11, 12 and 13. Furthermore, Bitcoin also experiences a significant reduction in volatility (-1.295), in response to the combination of all the regulatory announcements. Only events 1 and 7 (negative Chinese and South Korean announcements respectively) generate a significant increase in volatility for Bitcoin. Ethereum (Table 4) also experiences a significant reduction in overall volatility, in response to all regulation events (-1.867). Reductions in volatility are also observed after events 5, 7, 10, 12 and 13. Events 1, 3 and 8 generate an increase in volatility. In the case of Litecoin, only one coefficient indicates an increase in volatility, as illustrated in Table 5. The event in question (event 3) refers to the PBOC's decision to allow cryptocurrency exchange users to resume withdrawals. Events 6, 7, 8, 10 and 11 all generate a reduction in volatility. Once again, the overall response to the regulatory events (the all events coefficient of -1.594) is negative and significant. All three of the large-cap blockchain based coins (Bitcoin, Ethereum Litecoin) exhibit similar responses to the regulatory events. All three display a significant reduction in volatility to the combination of the events. Furthermore, these coefficients of -1.295, -1.867 and -1.594 are all similar in magnitude. In terms of the individual events, the coefficients of all three assets are predominantly negative. In the case of all three assets, five of the thirteen events generate a significant reduction in volatility. Significant volatility increases in response to individual events are observed only once in the cases of Ethereum and Litecoin, and just twice in the case of Bitcoin. Reported mean returns are found to fall significantly in all of events 1 through 11 as reported through coefficient relating to the the variable D_t in the mean equation.

Insert Table 6 about here

IOTA returns no significant results for the first five events examined (events 3 through 7. Data is not available during the periods covering events 1 and 2), however all subsequent events generate a significant coefficient (Table 6). Such a result indicates that, as IOTA has grown from its initial stages, it has become increasingly affected by the regulatory announcements in question, and indeed market forces as a whole. The first two of these significant coefficients, events 8 and 9 (a ban on exchange trading in mainland China and an SEC warning regarding ICOs in the U.S.), are positive, indicating an increase in volatility as a result of said announcements. The next four coefficients however, are all negative, indicating a reduction in volatility. With the exception of event 13, representing an announcement by the South Korean government that stated they would regulate rather than ban cryptocurrency trading, these four announcements were also predominantly negative, indicating that it was not the nature of the announcements themselves, which generated the change in direction of volatility. The fact that IOTA has moved from no exposure to volatility as a result of these announcements, to a consistent significant change in volatility, indicates that as IOTA has matured it has displayed a significant exposure to these external market forces that was not observed in the case of the large-cap blockchain based assets.

Insert Tables 7 and 8 about here

In the case of NANO, four events from a possible ten generate a significant change in volatility, as illustrated in Table 7. Events 4, 7 and 9 generate a significant increase in volatility. Particularly in the cases of events 7 and 9 (A South Korean ban on ICOs and an SEC warning on ICOs), these events were previously shown to generate no significant coefficients in the cases of the three large-cap blockchain based assets. Just one event generates a reduction in volatility - the announcement of a planned ICO ban in South Korea. As in the case of IOTA, the significant coefficient occurs after the significant positive coefficients, and a similar pattern is observed. It may be argued that the contents of, and market conditions surrounding, the later events were simply more suited to generating a reduction in volatility. This suggestion is supported by the fact that we observe similar coefficients in the cases of Bitcoin, Ethereum and Litecoin. However, the fact that, as they mature, these DAG based assets begin to show similar behaviour to the more established large-cap blockchain assets, is interesting in it's own right. Obyte displays a significant coefficient in the case of nine of the thirteen events (Table 8). These individual events are in addition to an overall coefficient of -2.521. Seven of the significant event coefficients are negative (events 5 through 8 and 11 through 13). The two positive coefficients, events 1 and 9, surround the warnings issued by the Chinese PBOC and the U.S. SEC respectively. In the case of the three DAG based assets, only one (Obyte) displays a significant overall coefficient. Neither IOTA nor NANO display evidence of a significant link between the full sample of regulatory announcements and volatility changes. This finding is in contrast to the large-cap blockchain based assets which all displayed a significant negative coefficient over the full sample. In the case of the Obyte, the coefficient is also negative, however, the magnitude is significantly larger than that of Bitcoin, Ethereum and Litecoin (-2.521).

Insert Tables 9, 10 and 11 about here

In the case of Verge, individual regulatory announcements generate significant volatility changes in seven out of thirteen events. These results are displayed in Table 9. As was observed in the case of Obyte, events 1 and 9 are the only cases in which there is an increase in volatility. The remaining significant events (5, 6, 10, 11 and 12) all generate a reduction in volatility. In terms of its reaction to the full set of announcements, Verge experiences a large, significant decrease in volatility (-3.244). This change is the largest of the nine assets in our sample and almost double all three of the large-cap blockchain assets. Qtum experiences a significant change in volatility in eight of eleven events (Table 10). After displaying just one significant result between events 1 to 4, all subsequent events generate a significant change. Just two events led to an increase in volatility (events 1 and 7), both of which were related to Asian announcements which were negative in nature. Events 5, 6, and 8 through 11 all generated a decrease in volatility. Despite this majority, the overall coefficient is found not to be significant. Our final asset, Factom, displays a significant change in volatility after seven of the thirteen events. Four announcements (5, 6, 7 and 13) generate negative coefficients, and all related to Asian markets. Events 3, 8 and 9 generate an increase in volatility, and again, all three announcements took place in Asia. Neither of the U.S. announcements are found to generate a significant volatility change. Finally, as illustrated by Table 11, Factom's response to the overall sample of events is a significant reduction in volatility. The coefficient of -1.667 is consistent with those observed in the group of large-cap blockchain assets. The group of medium-cap blockchain assets display similarities with that of the large-cap blockchain assets. Both Verge and Factom display an overall reduction in volatility, as a result of regulatory announcements. While the reduction in Verge volatility is significantly larger than any of the other assets in our sample, the change in Factom is consistent with those of Bitcoin, Ethereum and Litecoin. The Qtum coefficient ultimately lacks significance (despite a large proportion of individual events displaying significance), however, this may be due to a lack of reliable data for events 12 and 13.

Insert Figure 7 about here

Figure 7 summarises both the changes in volatility that occurred after each individual event and the overall change across the entire sample of events. In the case of event 1, the PBOC warning regarding Bitcoin, all six assets for which data was available displayed an increase in volatility. Such a result is expected, as a result of the increased trading that would follow such a negative announcement. Furthermore, this announcement took place in early 2017. Bitcoin has received a lot of mainstream attention in recent times, however as recently as January 2017, Bitcoin was still a relatively obscure product and a considerably smaller market. As such, an announcement such of this would have had a significantly larger effect on the market then, when compared to the effect a similar announcement would have today. Event 2, an announcement by the Japanese government to recognise Bitcoin as a legal currency, generates relatively minor changes in volatility. Of those assets which were affected, Bitcoin and Ethereum experienced the largest change. The DAG and medium-cap asset groups are relatively unaffected. Event 3, an announcement by the Chinese PBOC to allow exchange withdrawals, generates significant changes in volatility across most assets. In the case of Bitcoin, Ethereum and Litecoin, all three experience an increase in volatility. In the case of the DAG assets, both IOTA and Obyte experience a decrease in volatility. In the case of IOTA, this decrease (-3.837) is noticeable due to its size. Event 4, an intention by the SEC to regulate ICOs, has again generated relatively small amounts of volatility change. One asset, NANO, is an exception in this case and experiences an increase (1.361). Event 5, the banning of ICOs in China, results in a reduction in volatility across all assets. The magnitude of such decreases is reasonably consistent across all assets. Event 6, the closing of China's largest exchange following reports of an impending ban on all cryptocurrencies, generates a reduction in volatility across all assets, with the exception of Bitcoin. This suggests that, as the standard bearer for all cryptocurrencies, Bitcoin was the focus of most reaction to his announcement.

Event 7, a South Korean ban on ICOs, generated varying levels of response across assets. Both the large and medium-cap asset groups contained one asset which experienced a large decrease (Ethereum and Qtum respectively) however the changes among the DAG group of assets are relatively minor. The banning of exchange trading in mainland China, event 8, would be expected to generate significant changes in volatility levels, due to the wide-ranging consequences of such an action (at the time, China was the largest market participant and the vast majority of worldwide mining rigs were located in China). The relatively small volatility increase in Bitcoin is somewhat surprising. However, the large increase in Ethereum volatility (6.714) is as expected. While IOTA also experiences an increase in volatility, the other smaller DAG assets experience a small decrease (-0.232 for NANO, and -1.046 for Obyte). Event 9, an SEC warning regarding ICOs, cause a positive increase in volatility for all nine assets. The levels of increase are significantly larger in the cases of the DAG and medium-cap assets, suggesting that the more established assets (Bitcoin, Ethereum, Litecoin) were considerably less affected by this negative announcement. Both events 10 and 11 (announcements by both South Korea and China to ban and target online trading platforms, respectively) generated a reduction in volatility levels in all cases. Again, the levels are reasonably consistent across all assets and there are no notable exceptions. Event 12, the announcement of a ban on anonymous trading accounts in South Korea, generated a reduction in volatility among all assets, with the exception Litecoin. None of these assets are particularly targeted at users requiring anonymity. As such, we would expect a more notable volatility change in assets such as Monero and ZCash, both coins whose primary function is privacy. Event 13, a positive announcement by the South Korean government regarding their intention to regulate, rather than bad, cryptocurrency trading, generates large reductions in volatility among almost all assets in our sample (Litecoin is the exception). The levels for both Verge and Qtum are the largest observed in our entire sample. The levels observed among the DAG and large-cap groups are relatively similar.

With regard to the overall sample of events, seven out of the total nine assets experience a reduction in volatility levels. Changes in Bitcoin, Ethereum and Litecoin levels are all relatively similar (-1.295, -1.867 and -1.594 respectively). DAG based assets experience different levels of change. IOTA experiences a similar decrease in volatility (-1.022) a result which may be explained by the fact that it is a large-cap asset itself. IOTA is consistently ranked among the top 10 market caps of all cryptocurrencies. A similarity to the other larger assets, despite the difference in its underlying technology, is somewhat explained by this fact. Both NANO and Obyte however exhibit considerable differences in relation to the large-cap assets. NANO experiences an overall increase, while Obyte experiences a significantly larger decrease in volatility levels (-2.521). Group 2, the medium-cap blockchain assets bear more similarity to the DAG based asset group than the large-cap blockchain group.

Finally, we further examine our sample by constructing indicator variables, based on the country in which each of the announcements was made, and re-estimate our model. We find China and Korea to generate primarily negative volatility changes, while the USA generates primarily positive changes. Announcements made in Japan were primarily found to generate no changes in volatility.

Announcements regarding Japanese policy appear to have had the least effect on our sample. Only Bitcoin displays a statistically significant reaction. This result can be explained by the fact that, at the time of the announcement contained within this sample, Japan accounted for a relatively small percentage of worldwide cryptocurrency trading and mining. China, Korea, and Japan, however, all display a similar level of influence, with seven assets displaying a significant reaction to their respective announcements. Again, this result can be quantified by the fact that these three countries dominated the world cryptocurrency market at the time of this study. In the case of China, six assets displayed evidence of a reduction in volatility, following their regulatory announcements. Just Ethereum experienced an increase in volatility levels. A similar scenario is observed in the case of Korea, with all seven affected assets experiencing a decrease in volatility. In the case of the USA however, these results are reversed. Just one asset (Litecoin) experienced a significant reduction in volatility as a result of US regulatory announcements. The vast majority of the sample (Bitcoin, IOTA, NANO, Obyte, Qtum, and Factom) however, experienced an increase in volatility, a scenario which was not observed in the cases of Chinese or South Korean announcements.

6. How have these new technologies added value?

We have provided evidence which shows that DAG-based assets become increasingly responsive to market shocks as they mature. Such behaviour mirrors that of established cryptocurrencies such as Bitcoin, Ethereum and Litecoin, providing evidence that DAG-based cryptocurrencies now share similar characteristics to traditional blockchain-based products. Investors appear to now consider these products in the same manner as those 'traditional cryptocurrencies'. Following this finding, we investigate how these new technologies add value.

6.1. IOT Devices

IOT devices will have limit storage capacity, reducing their ability to store large amounts of data - a characteristic which would prevent such devices from acting as a full blockchain node. The Tangle overcomes this issue by removing the need for a consistent global state, as previously discussed with regard to CAP theorem. Each device takes a snapshot of the current state of the relevant area of the ledger. Devices are only concerned with the validity of the ledger, not the history, so they will remove all unnecessary historical data, resulting in a significantly smaller amount of data required to be stored. Each device is only required to store the current state. Partition tolerance allows this task to be performed locally. For most smaller nodes, maintaining snapshots will be sufficient, while it will fall upon larger nodes (permanodes) to store the entire ledger. IOT devices have neither the necessary storage, nor incentive, to store the entire tangle history. As an IOT device, it will only be required to validate the current state. All nodes are considered full nodes, regardless of whether they are storing the full history, or the current state. Any permanode storing the full history would theoretically need to be incentivised to do so. Such an incentive would be provided by any individual or corporation that required, or desired, access to the full history. Such a user would be willing to pay for this information, thus providing the incentive.

Data integrity is an important proponent of an IOT economy. Applications will receive over-air updates over The Tangle network (for instance, AI cars, which are required to receive updates over the network). A vulnerable network would leave such updates open to the possibility of a man-in-the-middle attack, in which an attacker may distribute a malicious update to the IOT devices. The data integrity provided by the tangle ensures safety across IOT devices. Bandwidth consumption problems arise when blockchain nodes are required to sync the entire blockchain, and constantly be fully updated. Such a requirement would be unpractical for IOT devices, and partition tolerance allows them to overcome this problem. Because IOT devices are not required to connect to, and constantly update with, the entire blockchain, they can communicate over mesh networks, reducing bandwidth concerns and keeping energy consumption significantly lower. IOT devices may only need to synchronise to the main network once a day, all other communication can be performed over these mesh networks.

Once IOT devices have been manufactured, it follows that software upgrades and enhancements will be necessary. Situations will arise in which a new proof-of-work algorithm needs to be introduced, or updated. Once this update has taken place, old IOT devices will still need to be compatible. In order for this process to be managed effectively, the network requires a standardised consensus protocol. Once a consensus with regard to the hashing function itself has been reached, developments which improve efficiency in integrated circuits will not be an issue to any existing devices - as the underlying hashing function will remain the same. As such, all devices will still be able to carry out transactions, with newer devices having improved efficiency over older existing ones. With regard to existing devices currently in circulation without any hashing devices, these devices will largely be incompatible with the network. This process is similar to the way in which old mobile phones eventually become incompatible with newer, more intensive, software updates. As such, the consensus must be established, and standardised, at an early stage, prior to the creation and manufacturing of widespread IOT devices.

In the current economy, data is increasingly relied upon for almost all decisions - both directly and indirectly. IOT devices will be involved in all aspects of life, from healthcare to infrastructure, to transport. An IOT economy will require the transfer and exchange of millions of data packets. As previously highlighted, the blockchain contains a number of inherent features that prevent it from scaling to accommodate the transfer of large amounts of such data packets. The blockchain already experiences difficulty relating to block sizes and delays , and struggles to accommodate simple transactions at a very early stage in its usage. Additionally, the presence of transactions fees upon the blockchain would make the transfer of such data implausible, due to the associated expenses. With transaction fees on the Bitcoin and Ethereum networks continually rising, the cost of transmitting a micro-transaction would far exceed the value of the data-packet itself. To avoid continued transaction fees, blockchain users are currently resorting to storing data, and combining it into one large packet, before sending it on the blockchain. While this reduces the associated cost, such a strategy would not be practical for IOT devices, which are required to transmit data in real-time. IOTA and The Tangle removes the need for such measures - due to the absence of the scaling problems associated with the blockchain - and so, can be used as a genuine data anchoring protocol. All sensor, device and machinery data, can be stored, and guaranteed not to be changed, on The Tangle. In the same manner as the blockchain, once data has been attached to the tangle ledger, it cannot be altered again. Applications can then be built on top of the protocol, in a similar manner to the decentralised applications currently being developed on the blockchain.

6.2. Fog Computing

As the IOT economy expands, semi-conductor manufacturers will position themselves to add value and take advantage of this new industry - using technology such as The Tangle. A primary use case of the tangle and IOTA is fog computation and fog storage. Cloud storage, in its current form, involves huge data centres located across the world, which contain and store all user's data on large centralised servers. As the IOT economy progresses, cloud storage facilities will be required to shift further away from dense centralised data centres to a more decentralised model. Fog computing refers to a distributed version of the cloud, characterised by numerous smaller geographically dispersed computation centres as opposed to large central data centres. In an IOT economy, millions of devices are required to relay data in real-time. Millions of IOT sensors simultaneously attempting to relay data to a large cloud storage centre would not be practical, due to restrictions imposed by bandwidth limits and signal interference. It becomes necessary for the data to be distributed in some manner. Smaller centres, which are strategically located close to areas with large concentration of IOT devices, must be distributed geographically. Instead of each device communicating with the same central centre, each device can communicate with the smaller, geographically local, computation station. The relayed information can then be analysed locally, by the smaller station, condensed and combined into a large data packet, and relayed to the cloud itself. In this manner, the number of data transfers to the central data centre itself is greatly reduced; without the loss, or restriction, of any data transfer. IOTA and The Tangle facilitate the transfer of data between such centres, by removing the need for time consuming subscription services. The ownership of local data centres may be distributed among thousands of stakeholders. In its current form, each sensor would be required to enter into a subscription agreement with the fog service provider themselves. With millions of IOT devices existing, such a service would be time consuming, expensive, and impractical. Instead, IOTA facilitates machine-to-machine payments - between devices and the fog computational centres - by allowing IOT devices to directly pay the centre themselves. As well as reducing network congestion, fog storage allows limited-storage IOT devices to purchase additional storage capacity. Such a practice could also be facilitated by The Tangle. A machine economy appears inevitable, and it will fall upon hardware manufacturers to ensure that their devices can accommodate such a system, and the appropriate software. In its current form, IOTA is the only software which would be capable of facilitating the above scenario.

6.3. Strategic Advantages Over the Blockchain

6.3.1. Scaling

The current blockchain suffers from a number of flaws, namely; its inability to scale, and the high transaction fees associated with it. These flaws lead to limitations in the future development of the blockchain and prohibit a number of potential use cases. In the case of transfer of micro-data packets - which may each be worth a minuscule amount - use of a blockchain in its current form would be highly inefficient, as the transaction cost that would be required to transfer each data packet would far outweigh the value of the data itself. A new architecture is necessary, one with the same core features as the blockhain, but which facilitates and enables the above type of transactions. The Tangle provides such a solution through the use of a directed acyclic graph (DAG).

The Tangle addresses the scalability issues of blockchain, and imposes no finite limit to transactions per minute on the network[9]. Due to the nature of the DAG, an increase in transactions imposed on the network, simultaneously results in a corresponding increase in validation (twice the rate of new transactions). The removal of any limits on the network, such as the blocksize limits currently imposed on the blockchain, means that there is no inherent limit to transactions or validations per minute on the IOTA network.

6.3.2. Transaction Fees

The use of a DAG removes one of the inherent limiting factors of the blockchain, by decoupling usage and validation. In its current structure, user incentives are opposed: validators are incentivised by potential earnings from block rewards and transaction fees; a user's primary goal is to conduct transactions as quickly and cheaply as possible. Limited block sizes lead to a supply and demand equilibrium between participants, and result in a gradual increase in transaction fees - particularly during a period of high volume on the network. IOTA re-couples these two actions in the tangle, in such a manner that the user also becomes the validator. Such a system removes

[9]IOTA has already proven capable of accepting up to 400 transactions per second on test networks. On average, the Bitcoin network is capable of accepting between 4 and 7 transactions per second

the need for miners to validate, and as such, removes the need for any transaction fees. Validation becomes an intrinsic property of network. Despite its claims to the contrary, a blockchain, in its current form, lends itself to centralisation. While the need for a centralised authority has been removed, the blockchain begins to centralised around the small number of mining pools that control the majority of the network. The use of The Tangle removes the possibility of this happening.

6.3.3. Economic Incentives

The use of a DAG removes one of the inherent limiting factors of the blockchain, by decoupling usage and validation. In its current structure, user incentives are opposed: validators are incentivised by potential earnings from block rewards and transaction fees; a user's primary goal is to conduct transactions as quickly and cheaply as possible. Limited block sizes lead to a supply and demand equilibrium between participants, and result in a gradual increase in transaction fees - particularly during a period of high volume on the network. IOTA re-couples these two actions in The Tangle, in such a manner that the user also becomes the validator. Such a system removes the need for miners to validate, and as such, removes the need for any transaction fees. Validation becomes an intrinsic property of network. Despite its claims to the contrary, a blockchain, in its current form, lends itself to centralisation. While the need for a centralised authority has been removed, the blockchain begins to centralised around the small number of mining pools that control the majority of the network. The use of The Tangle removes the possibility of this happening.

6.3.4. Quantum Computing Resistance

Quantum computing is a rapidly growing technology that has the potential to overhaul the computing industry, and the blockchain. The cryptographic technology behind most blockchain methods means they could easily be compromised by the use of quantum computers. Private keys which were previously considered secure, could be obtained by a quantum computer in a manner of seconds. IOTA, and The Tangle, are quantum resistant, meaning that such methods would prove ineffective in undermining the security of the network.

Although still a theory, quantum computing is a fast-developing area, and some small prototypes have already begun to be built. Quantum computing possesses the ability to render most current cryptography methods useless, and as a result, impact the security of cryptocurrencies. For this reason, future cryptocurrencies will be required to use cryptography methods that are are immune to, and unbreakable by, these quantum computers. One such method, and the method used in

The Tangle, is the use of Winternitz signatures [Winternitz, 1984a,b]. Most algorithms currently used in blockchain technology to generate public and private keys, are based upon the solving of complex mathematical problems. Such problems include elliptic-curve discrete logs and integer factorisation, and rely on the fact that they require large amounts of processing effort to solve. However, using Shor's algorithm[10], any of these methods could be easily solved by a quantum computer. Current blockchain methods could be upgraded to quantum resistant ones, by means of a hard fork, however, as the Bitcoin Segwit debate has previously demonstrated, such forks are not easy to agree upon. The previously discussed shared incentives among all users of The Tangle network, mean that demands of the hashing algorithms can be made significantly less intensive. The Winternitz signature hash method remains resistant to potential quantum computer methods, as they would not significantly lower the security of the hashes. When compared with Bitcoin, The Tangle requires a significantly smaller number of nonces to be checked before finding a correct hash that will enable the generation of a new block. When compared with traditional computing methods, quantum computing would be approximately 17 billion times more efficient in Bitcoin mining, due to this large number of computations required to generate a correct hash. However, because IOTA requires a significantly less amount of nonce checks due to the reduced hashing difficulty requirements - and therefore significantly less computation power - the gain for a quantum computer over traditional computing methods would be significantly less (approximately 80 times more efficient). The use of a quantum computer would be significantly less effective on a network using The Tangle, such as IOTA.

7. Conclusion

Directed acyclic graphs are an increasingly valuable substitution for blockchain technology. They possess a number of key strategic advantages over blockchains, namely their lack of transaction fees and increased speeds. As such, DAG-based assets facilitate the use of micro-transactions and are more appropriate for use with IOT devices, in the impending machine economy. The rise of such IOT devices will only continue, and this could be a major factor in an ensuing rise in popularity

[10]Shor's algorithm, presented in 1994 by Peter Shor, refers to a quantum algorithm for integer factorisation. The algorithm finds the period of the function using the quantum Fourier transform, which results in a considerable increase in speed. The use of this algorithm could be applied to some cryptographic methods and effectively render them useless. [Shor, 1994]

among DAG-based assets. Regardless, their potential for use in fog computing, as well as their resistance to quantum computing mean that DAGs, as an alternative to blockchains, should become considerably more prominent over the coming years. Three such assets that already employ DAGs are IOTA, NANO and Obyte. All three assets are built around a different data structure (The Tangle, a Block Lattice and a Main-Chain) and are resistant to quantum computing, meaning they already possess an important long-term advantage over currencies such as Bitcoin, Ethereum and Litecoin. Having examined the volatility reaction of these groups of currencies to market shock events (in the form of regulatory announcements) we have shown that currencies such as IOTA have begun to display similar reactions to those of large-cap blockchain based assets, particularly as they have matured. DAG-based assets therefore appear an appropriate substitution for their blockchain based equivalents and, with their variety of advantages and potential use cases, look set to become increasingly prominent in the future.

References

Akhtaruzzaman, M., A. Sensoy, and S. Corbet (2019). The influence of bitcoin on portfolio diversification and design. *Finance Research Letters*, 101344.

Akyildirim, E., S. Corbet, P. Katsiampa, N. Kellard, and A. Sensoy (2019). The development of bitcoin futures: Exploring the interactions between cryptocurrency derivatives. *Finance Research Letters In Press, Available at: https://doi.org/10.1016/j.frl.2019.07.007.*

Akyildirim, E., S. Corbet, B. Lucey, A. Sensoy, and L. Yarovaya. The relationship between implied volatility and cryptocurrency returns. *Finance Research Letters In Press, Available at: https://doi.org/10.1016/j.frl.2019.06.010.*

Antonakakis, N., I. Chatziantoniou, and D. Gabauer (2019). Cryptocurrency market contagion: Market uncertainty, market complexity, and dynamic portfolios. *Journal of International Financial Markets, Institutions and Money 61*, 37–51.

Baur, D. G., T. Dimpfl, and K. Kuck (2017). Bitcoin, gold and the us dollar–a replication and extension. *Finance Research Letters*.

Baur, D. G., K. Hong, and A. D. Lee (2017). Bitcoin: Medium of exchange or speculative assets? *Journal of International Financial Markets, Institutions and Money*.

Birz, G. and J. R. Lott (2011). The effect of macroeconomic news on stock returns: New evidence from newspaper coverage. *Journal of Banking and Finance 35*(11), 2791–2800.

Bollerslev, T. (1986). Generalized autoregressive conditional heteroskedasticity. *Journal of Econometrics 31*, 307–327.

Brandvold, M., P. Molnár, K. Vagstad, and O. C. A. Valstad (2015). Price discovery on bitcoin exchanges. *Journal of International Financial Markets, Institutions and Money 36*, 18–35.

Brauneis, A. and R. Mestel (2018). Price discovery of cryptocurrencies: Bitcoin and beyond. *Economics Letters*.

Brière, M., K. Oosterlinck, and A. Szafarz (2015). Virtual currency, tangible return: Portfolio diversification with bitcoin. *Journal of Asset Management 16*(6), 365–373.

Corbet, S., V. Eraslan, B. Lucey, and A. Sensoy (2019). The effectiveness of technical trading rules in cryptocurrency markets. *Finance Research Letters 31*, 32–37.

Corbet, S. and P. Katsiampa (2018). Asymmetric mean reversion of Bitcoin price returns. *International Review of Financial Analysis In Press, Available at: https://doi.org/10.1016/j.irfa.2018.10.004*.

Corbet, S., C. Larkin, B. Lucey, A. Meegan, and L. Yarovaya (2018). Exploring the dynamic relationships between cryptocurrencies and other financial assets. *Economics Letters 165*(1), 28–34.

Corbet, S., C. Larkin, B. Lucey, A. Meegan, and L. Yarovaya (2020a). Cryptocurrency reaction to FOMC announcements: Evidence of heterogeneity based on blockchain stack position. *Journal of Financial Stability 46*, 100706.

Corbet, S., C. Larkin, B. Lucey, A. Meegan, and L. Yarovaya (2020b). The volatility generating effects of macroeconomic news on cryptocurrency returns. *European Journal of Finance Forthcoming*.

Corbet, S., C. Larkin, B. Lucey, and L. Yarovaya (2020). Kodakcoin: a blockchain revolution or exploiting a potential cryptocurrency bubble? *Applied Economics Letters*, 1–7.

Corbet, S., B. Lucey, A. Urquhart, and L. Yaravaya (2019). Cryptocurrencies as a financial asset: A systematic analysis. *International Review of Financial Analysis 62*, 182–199.

Corbet, S., B. Lucey, and L. Yarovya (2018). Datestamping the Bitcoin and Ethereum bubbles. *Finance Research Letters 26*(1), 81–88.

Corbet, S., G. McHugh, and A. Meegan (2018). The influence of central bank monetary policy announcements on cryptocurrency return volatility. *Investment management and financial innovations* (14, Iss. 4), 60–72.

Dwyer, G. P. (2015). The economics of bitcoin and similar private digital currencies. *Journal of Financial Stability 17*, 81–91.

Dwyer, G. P. (2017). Blockchain: a primer. In *The Most Important Concepts in Finance*. Edward Elgar Publishing.

Dyhrberg, A. H. (2016a). Bitcoin, gold and the dollar–a garch volatility analysis. *Finance Research Letters 16*, 85–92.

Dyhrberg, A. H. (2016b). Hedging capabilities of bitcoin. is it the virtual gold? *Finance Research Letters 16*, 139–144.

Feld, S., M. Schönfeld, and M. Werner (2014). Analyzing the deployment of bitcoin's p2p network under an as-level perspective. *Procedia Computer Science 32*, 1121–1126.

Hayes, A. S. (2017). Cryptocurrency value formation: An empirical study leading to a cost of production model for valuing bitcoin. *Telematics and Informatics 34*(7), 1308–1321.

Iwamura, M., Y. Kitamura, T. Matsumoto, and K. Saito (2014). Can we stabilize the price of a cryptocurrency?: Understanding the design of bitcoin and its potential to compete with central bank money.

Katsiampa, P., S. Corbet, and B. Lucey (2019). Volatility spillover effects in leading cryptocurrencies: A bekk-mgarch analysis. *Finance Research Letters 29*, 68–74.

Marimon, R., J. P. Nicolini, and P. Teles (2012). Money is an experience good: Competition and trust in the private provision of money. *Journal of Monetary Economics 59*(8), 815–825.

Nadarajah, S. and J. Chu (2017). On the inefficiency of bitcoin. *Economics Letters 150*, 6–9.

Nakamoto, S. (2008). Bitcoin: A peer-to-peer electronic cash system.

Phillips, P. C., Y. Wu, and J. Yu (2011). Explosive behavior in the 1990s nasdaq: When did exuberance escalate asset values? *International Economic Review 52*(1), 201–226.

Popov, S. (2016). The tangle. *cit. on*, 131.

Shor, P. W. (1994). Algorithms for quantum computation: Discrete logarithms and factoring. In *Foundations of Computer Science, 1994 Proceedings., 35th Annual Symposium on*, pp. 124–134. Ieee.

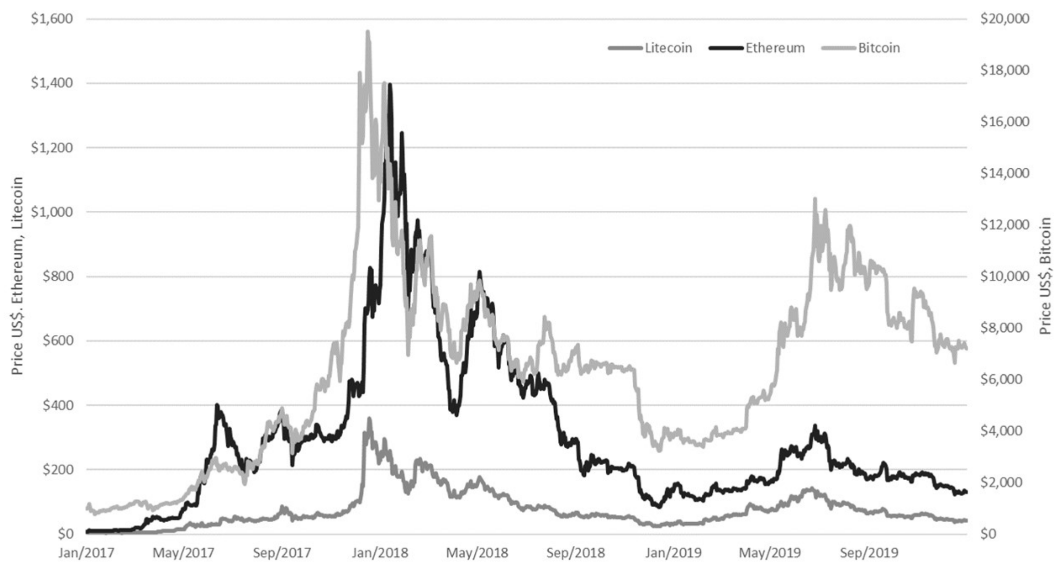
Tiwari, A. K., R. Jana, D. Das, and D. Roubaud (2018). Informational efficiency of bitcoin—an extension. *Economics Letters 163*, 106–109.

Walther, T., T. Klein, and E. Bouri (2019). Exogenous drivers of bitcoin and cryptocurrency volatility – a mixed data sampling approach to forecasting. *Journal of International Financial Markets, Institutions and Money 63*.

Winternitz, R. S. (1984a). Producing a one-way hash function from des. In *Advances in Cryptology*, pp. 203–207. Springer.

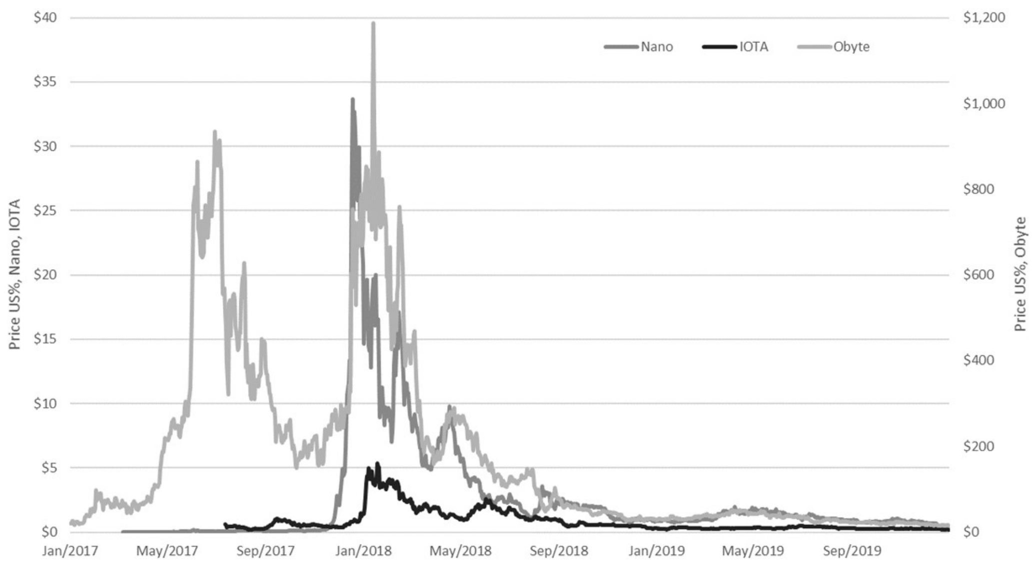
Winternitz, R. S. (1984b). A secure one-way hash function built from des. In *Security and Privacy, 1984 IEEE Symposium on*, pp. 88–88. IEEE.

Figure 1: Daily Closing Price of High-Cap Blockchain-Based Digital Assets; 2017-2019



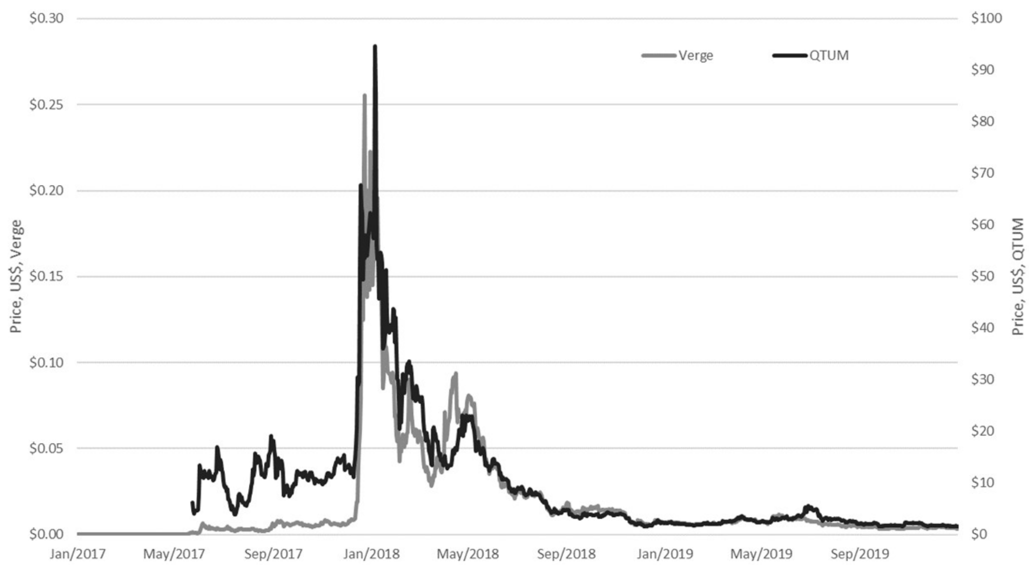
Note: Figure shows the daily closing prices of Bitcoin, Ethereum and Litecoin, from January 2017 - December 2019. Bitcoin, Ethereum and Litecoin are all blockchain-based networks. Blockchain technology refers to a distributed public ledger which is used to record transactions between network participants. The ledger uses blockchain technology to achieve consensus. A blockchain is secured by "miners" who facilitate the addition of new blocks to the chain, and in doing so, secure the network.

Figure 2: Daily Closing Price of DAG-Based Digital Assets; 2017-2019



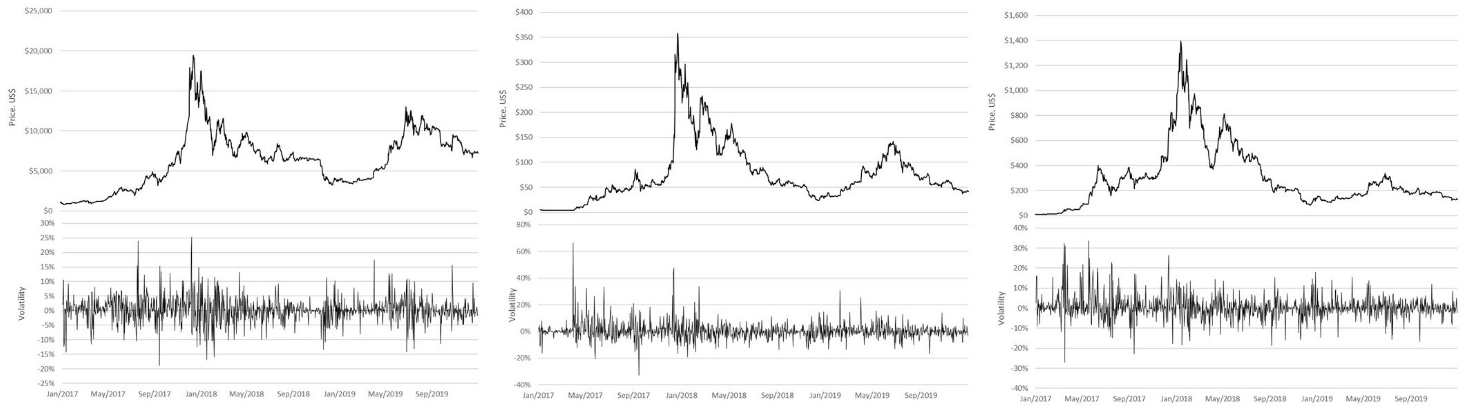
Note: Note: Figure shows the daily closing prices of IOTA, NANO and Obyte (formerly Byteball) from January 2017 - December 2019. IOTA, NANO and Obyte (formerly Byteball) are all DAG(directed acyclic graph)-based networks. DAG technology refers to a distributed public ledger which is used to record transactions between network participants.The ledger uses DAG technology to achieve consensus. A DAG consists of a series of vertices and edges with uniform direction. A DAG-based network is secured by each individual participant, each time they issue a new transaction.

Figure 3: Daily Closing Price of Medium-Cap Blockchain-Based Digital Assets; 2017-2019



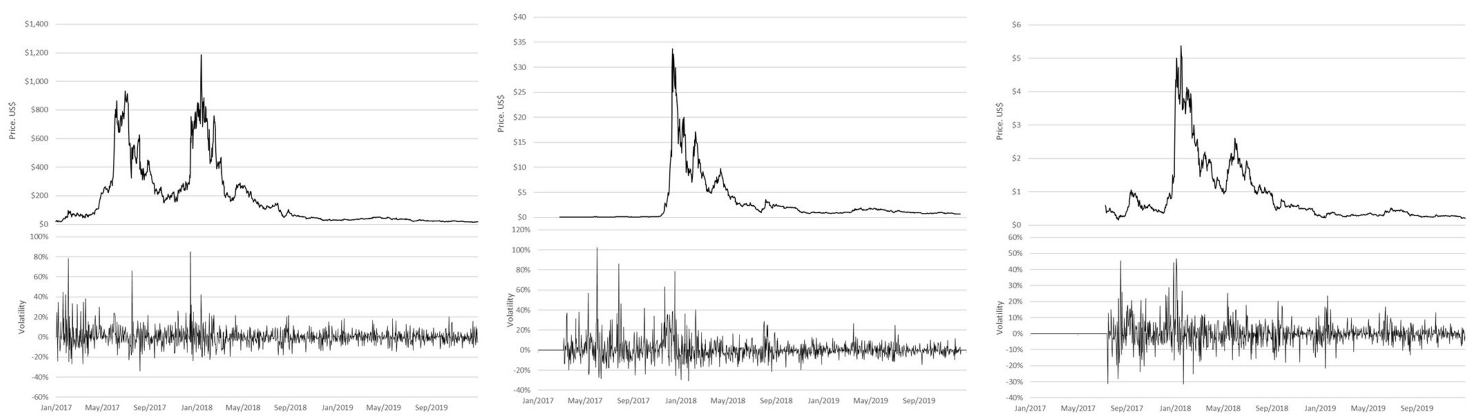
Note: Figure shows the daily closing prices of Qtum and Verge, from January 2017 - December 2019. Qtum and Verge are both blockchain-based networks. Blockchain technology refers to a distributed public ledger which is used to record transactions between network participants. A blockchain is secured by "miners" who facilitate the addition of new blocks to the chain, and in doing so, secure the network.

Figure 4: Daily Closing Price & Daily Percentage Change in the Closing Price of High-Cap Blockchain-Based Assets



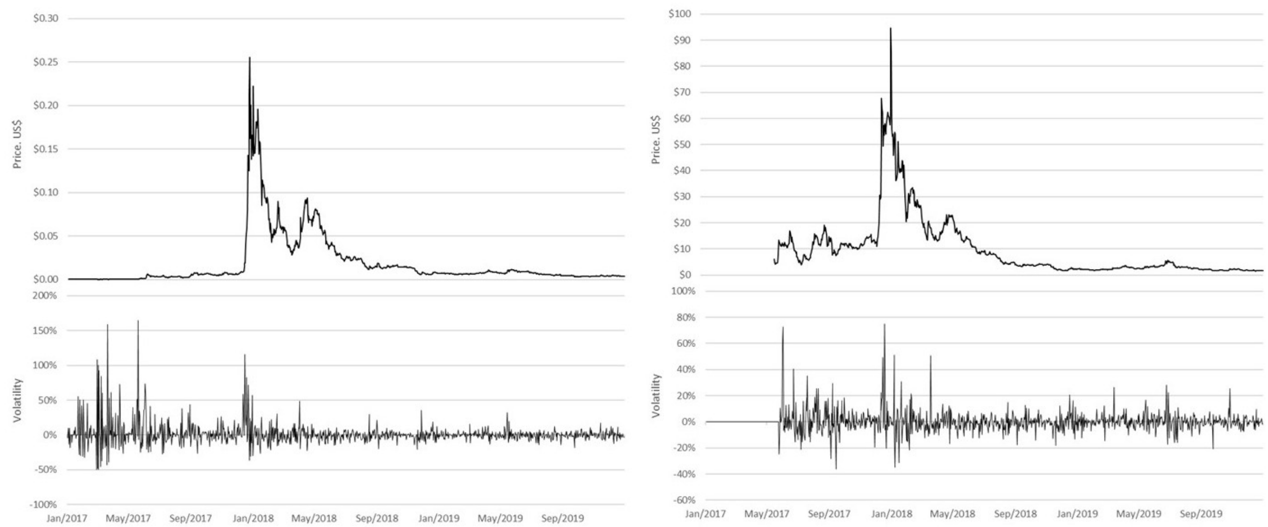
Note: The top panel shows the daily closing prices of Bitcoin, Ethereum and Litecoin. Bottom panel show the daily percentage change in the prices of Bitcoin, Ethereum and Litecoin. These three assets are all blockchain-based.

Figure 5: Daily Closing Price & Daily Percentage Change in the Closing Price of DAG-Based Assets



Note: The top panel shows the daily closing prices of IOTA, NANO and Obyte (formerly Byteball). Bottom panel show the daily percentage change in the prices of IOTA, NANO and Obyte (formerly Byteball). These three assets are all DAG(directed acyclic graph)-based.

Figure 6: Daily Closing Price & Daily Percentage Change in the Closing Price of Medium-Cap Blockchain-Based Assets



Note: The top panel shows the daily closing prices of Qtum and Verge. Bottom panel show the daily percentage change in the prices of Qtum and Verge. These three assets are all Blockchain-based.

Figure 7: Estimated EGARCH volatility change based on the selected dummy variable for each regulatory event

	Group 1			Group 2			Group 3		
	BTC	ETH	LTC	Verge	Qtum	Factom	IOTA	NANO	Byte
Event 1	1.178	2.642	0.190	2.750		0.434			1.669
Event 2	-0.842	1.196	-0.642	-0.396		-0.613		0.003	-0.427
Event 3	0.090	2.11	1.189	-1.504	1.280	0.654	-3.837	0.659	-1.120
Event 4	0.020	0.053	-0.272	0.117	0.106	0.201	-0.062	1.361	-0.129
Event 5	-1.393	-1.789	-1.272	-3.158	-1.114	-1.835	-1.543	-0.497	-2.280
Event 6	0.199	-0.589	-0.896	-1.557	-3.839	-1.754	-0.574	-0.581	-1.878
Event 7	0.911	-3.24	-0.964	-0.856	-3.338	-1.395	-0.327	0.404	-1.451
Event 8	0.354	6.714	-1.491	-2.014	-2.363	0.810	2.460	-0.232	-1.046
Event 9	0.240	0.342	0.214	3.305	3.845	0.886	1.004	0.926	1.345
Event 10	-2.454	-0.56	-1.839	-2.977	-0.890	-0.786	-1.466	-1.400	-0.019
Event 11	-3.053	-1.138	-1.736	-0.442	-0.893	-0.947	-1.578	-1.033	-1.394
Event 12	-1.290	-1.708	0.287	-1.660	-2.851	-0.964	-1.781	-0.884	-1.187
Event 13	-1.238	-2.801	0.648	-7.495	-5.182	-0.628	-2.678	-1.705	-1.749
All Events	-1.295	-1.867	-1.594	-3.244	0.683	-1.667	-1.022	0.312	-2.521

Note: The top panel shows the daily closing prices of Qtum and Verge. Bottom panel show the daily percentage change in the prices of Qtum and Verge. These three assets are all Blockchain-based.

Table 1: List of major regulatory announcements based on cryptocurrency markets

Date	Explanation of Regulatory Announcement	Country of Origin
09/01/2017	1. PBOC* issued a number of warnings regarding Bitcoin	China
01/04/2017	2. Japanese government issues bill which recognises Bitcoin as legal currency	Japan
01/06/2017	3. Chinese Exchanges allow withdrawals again. PBOC indicated it was not forbidden	China
25/07/2017	4. SEC announces that some ICOs are securities and will be subject to agency regulation	USA
04/09/2017	5. PBOC ban all ICOs	China
14/09/2017	6. Reports circulate that PBOC will ban all cryptocurrency exchanges. China's largest exchange closes.	China
29/09/2017	7. South Korea announces ban on ICOs	South Korea
02/11/2017	8. Cryptocurrency exchange trading banned in mainland China	China
11/12/2017	9. SEC issue warning and announce crackdown on ICOs	USA
11/01/2018	10. South Korea announce plan to ban cryptocurrency trading	South Korea
15/01/2018	11. PBOC announce they will target online platforms that offer "exchange-like services"	China
23/01/2018	12. South Korea announce plan to ban the use of anonymous accounts to trade cryptocurrency	South Korea
31/01/2018	13. Korean Finance Minister states that they will regulate, rather than ban, cryptocurrency trading	South Korea

Note: The above table presents a list of the major regulatory announcements that have been made based on international cryptocurrency markets, such as declarations of intentions by sovereign states to outright ban their use and trading. *PBOC denotes the People's Bank of China.

Table 2: Summary statistics for selected cryptocurrency markets

Summary Statistics based on the price levels of cryptocurrency returns									
Levels	Bitcoin	Ethereum	Litecoin	Verge	Qtum	Factom	Iota	Nano	Obyte
Mean	6,887.5	285.816	70.302	0.015	7.139	10.564	0.605	2.115	146.236
Variance	11,790,477.7	50,218.0	2,885.367	0.001	114.828	131.180	0.648	16.464	41,650.6
Std.Dev.	3,433.7	224.094	53.716	0.029	10.716	11.453	0.805	4.058	204.085
Skewness	0.181	1.848	1.980	3.858	3.329	2.129	2.837	4.103	2.090
Kurtosis	-0.002	3.943	4.908	18.016	13.936	5.665	8.979	20.076	3.820
Minimum	777.760	8.170	3.710	0.000	0.000	1.240	0.000	0.000	11.550
Maximum	19,497.4	1,396.4	358.340	0.255	94.670	76.070	5.370	33.700	1,187.1
Summary Statistics based on the volatility of cryptocurrency returns									
Volatility	Bitcoin	Ethereum	Litecoin	Verge	Qtum	Factom	Iota	Nano	Obyte
Mean	0.0027	0.0044	0.0036	0.0122	0.0021	0.0023	0.0017	0.0078	0.0036
Variance	0.0018	0.0033	0.0040	0.0207	0.0060	0.0059	0.0046	0.0099	0.0077
Std.Dev.	0.0426	0.0576	0.0634	0.1438	0.0774	0.0766	0.0681	0.0994	0.0879
Skewness	-0.1403	0.4104	1.9190	4.0354	2.2131	0.5057	0.8216	2.5028	1.8929
Kurtosis	7.7944	6.4570	16.5937	34.1669	20.9109	3.3358	8.7320	18.1466	15.1903
Minimum	-0.3717	-0.4235	-0.3617	-0.5000	-0.4433	-0.3760	-0.4193	-0.4434	-0.3991
Maximum	0.2525	0.3366	0.6659	1.6467	0.7505	0.3954	0.4681	1.0236	0.8508

Note: The above table presents the summary statistics for each price levels and volatility of the cryptocurrencies selected for analysis in this research.

Table 3: Results of selected EGARCH-methodology based on regulatory announcement affects on Bitcoin returns

	Mean Eq.							Variance Eq.		
	R_{t-1}	R_{t-2}	R_{t-3}	S_t	S_{t-1}	S_{t-2}	D_t	D_t	EARCH	EGARCH
All Events	0.212***	0.051	0.159**	-0.467	-0.567	0.058	-0.155***	-1.295***	0.087**	0.844***
	(0.061)	(0.063)	(0.057)	(0.372)	(0.474)	(0.410)	(0.054)	(0.298)	(0.030)	(0.039)
Event 1	0.233***	0.081	0.148*	-0.503	-0.457	0.133	-0.459***	1.178**	0.228***	0.731***
	(0.068)	(0.065)	(0.062)	(0.355)	(0.450)	(0.407)	(0.052)	(0.410)	(0.061)	(0.065)
Event 2	0.235***	0.075	0.151*	-0.525	-0.461	0.088	-0.339***	-0.842	0.199***	0.764***
	(0.067)	(0.063)	(0.062)	(0.366)	(0.460)	(0.422)	(0.055)	(1.075)	(0.057)	(0.061)
Event 3	0.236***	0.077	0.154*	-0.51	-0.456	0.099	-0.386***	0.09	0.208***	0.760***
	(0.067)	(0.065)	(0.063)	(0.364)	(0.465)	(0.411)	(0.054)	(1.052)	(0.059)	(0.061)
Event 4	0.236***	0.077	0.154*	-0.511	-0.456	0.101	-0.391***	0.02	0.208***	0.761***
	(0.068)	(0.065)	(0.063)	(0.364)	(0.483)	(0.413)	(0.054)	(0.724)	(0.059)	(0.060)
Event 5	0.266***	0.093	0.170**	-0.488	-0.370	0.249	-0.513***	-1.393***	0.166**	0.718***
	(0.071)	(0.070)	(0.062)	(0.441)	(0.537)	(0.512)	(0.066)	(0.364)	(0.056)	(0.082)
Event 6	0.237***	0.077	0.155*	-0.512	-0.459	0.101	-0.399***	0.199	0.207***	0.765***
	(0.068)	(0.065)	(0.062)	(0.361)	(0.461)	(0.408)	(0.053)	(0.440)	(0.058)	(0.059)
Event 7	0.244***	0.077	0.156*	-0.51	-0.453	0.099	-0.381***	0.911*	0.211***	0.765***
	(0.066)	(0.063)	(0.061)	(0.348)	(0.450)	(0.396)	(0.051)	(0.449)	(0.057)	(0.057)
Event 8	0.233***	0.078	0.155*	-0.518	-0.46	0.102	-0.406***	0.354	0.205***	0.767***
	(0.067)	(0.066)	(0.062)	(0.366)	(0.459)	(0.404)	(0.053)	(0.521)	(0.058)	(0.059)
Event 9	0.237***	0.078	0.154*	-0.514	-0.46	0.096	-0.385***	0.24	0.211***	0.754***
	(0.067)	(0.065)	(0.063)	(0.366)	(0.468)	(0.426)	(0.054)	(1.241)	(0.060)	(0.066)
Event 10	0.291***	0.106	0.151*	-0.462*	-0.640*	0.120	-1.025***	-2.454*	0.299***	0.514***
	(0.070)	(0.054)	(0.061)	(0.233)	(0.325)	(0.241)	(0.042)	(1.089)	(0.082)	(0.099)
Event 11	0.286***	0.112*	0.143*	-0.498*	-0.454	0.226	-0.186***	-3.053*	0.288***	0.522***
	(0.071)	(0.053)	(0.061)	(0.217)	(0.265)	(0.200)	(0.029)	(1.318)	(0.079)	(0.097)
Event 12	0.291***	0.112*	0.148*	-0.389	-0.649	0.081	0.291	-1.290***	0.327***	0.456***
	(0.068)	(0.054)	(0.061)	(0.282)	(0.411)	(0.314)	(0.041)	(0.354)	(0.085)	(0.101)
Event 13	0.291***	0.107*	0.147*	-0.331	-0.651	0.081	0.310	-1.238**	0.345***	0.447***
	(0.067)	(0.053)	(0.061)	(0.307)	(0.410)	(0.322)	(0.042)	(0.400)	(0.086)	(0.098)

Note: The estimated model EGARCH model has the following form: $R_t = a_0 + \sum_{j=1}^{n} b_j R_{t-n} + b_2 S\&P500_t + \varepsilon_t + D_t$ where $\ln(h_t^2) = \omega + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) + \beta \ln(h_{t-1}^2) + D_t$ and where $R_{i,t}$ represents the return on asset i at time t and R_{t-1} represents the first lag of returns r_t. $b_2 S\&P500_t$ represents the return on the S&P500 index and it included as a proxy for market effects. Finally, D_t is included in the variance equation to provide a coefficient relating to the volatility response to the thirty-day period after each identified event.Standard errors are presented in parentheses. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

Table 4: Results of selected EGARCH-methodology based on regulatory announcement affects on Ethereum returns

	Mean Eq.				Variance Eq.		
	R_{t-1}	R_{t-2}	S_t	D_t	D_t	EARCH	EGARCH
All Events	0.122	0.180***	0.088	-0.206***	-1.867***	0.133***	0.859***
	(0.065)	(0.054)	(0.065)	(0.098)	(1.007)	(0.027)	(0.020)
Event 1	0.131*	0.197***	0.075	-0.200***	2.642**	0.110***	0.877***
	(0.065)	(0.050)	(0.067)	(0.031)	(0.838)	(0.021)	(0.013)
Event 2	0.124	0.200***	0.085	-0.211***	1.196	0.111***	0.880***
	(0.066)	(0.052)	(0.067)	(0.014)	(2.153)	(0.021)	(0.013)
Event 3	0.173**	0.183***	0.077	-0.355***	2.110**	0.245***	0.750***
	(0.063)	(0.042)	(0.060)	(0.097)	(0.704)	(0.051)	(0.037)
Event 4	0.217***	0.040	0.116**	-0.272***	0.053	0.205*	0.740***
	(0.037)	(0.056)	(0.042)	(0.017)	(0.362)	(0.090)	(0.141)
Event 5	0.173***	0.016	0.129**	-0.091***	-1.789*	0.128	0.722***
	(0.039)	(0.058)	(0.039)	(0.019)	(0.712)	(0.099)	(0.148)
Event 6	0.125	0.198***	0.083	-0.203***	-0.589	0.122***	0.819***
	(0.066)	(0.052)	(0.065)	(0.018)	(2.219)	(0.021)	(0.014)
Event 7	0.173**	0.179***	0.066	-0.240***	-3.240***	0.230***	0.762***
	(0.064)	(0.042)	(0.062)	(0.027)	(1.137)	(0.052)	(0.039)
Event 8	0.134*	0.214***	0.080	-0.261***	6.714***	0.163***	0.803***
	(0.064)	(0.043)	(0.060)	(0.082)	(0.447)	(0.028)	(0.019)
Event 9	0.183**	0.203***	0.081	-0.409***	0.342	0.232***	0.742***
	(0.063)	(0.042)	(0.062)	(0.017)	(1.759)	(0.048)	(0.037)
Event 10	0.185***	0.013	0.104**	-0.220***	-0.560*	0.168	0.795***
	(0.036)	(0.055)	(0.040)	(0.058)	(0.730)	(0.090)	(0.159)
Event 11	0.205***	0.021	0.122**	-0.385***	-1.138	0.180*	0.746***
	(0.036)	(0.055)	(0.040)	(0.039)	(0.602)	(0.090)	(0.141)
Event 12	0.196***	0.021	0.122**	-0.423***	-1.708*	0.177	0.746***
	(0.036)	(0.054)	(0.039)	(0.089)	(0.751)	(0.091)	(0.139)
Event 13	0.187***	0.010	0.132***	-0.463***	-2.801*	0.133	0.776***
	(0.035)	(0.054)	(0.038)	(0.046)	(1.403)	(0.086)	(0.143)

Note: The estimated model EGARCH model has the following form: $R_t = a_0 + \sum_{j=1}^{n} b_j R_{t-n} + b_2 S\&P500_t + \varepsilon_t + D_t$ where $\ln(h_t^2) = \omega + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) + \beta \ln(h_{t-1}^2) + D_t$ and where $R_{i,t}$ represents the return on asset i at time t and R_{t-1} represents the first lag of returns r_t. $b_2 S\&P500_t$ represents the return on the S&P500 index and it included as a proxy for market effects. Finally, D_t is included in the variance equation to provide a coefficient relating to the volatility response to the thirty-day period after each identified event.Standard errors are presented in parentheses. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

Table 5: Results of selected EGARCH-methodology based on regulatory announcement affects on Litecoin returns

	Mean Eq.				Variance Eq.		
	R_{t-1}	R_{t-2}	s_t	D_t	D_t	EARCH	EGARCH
All Events	0.052	0.029	-0.221	-1.293***	-1.594***	0.017	0.831***
	(0.066)	(0.060)	(0.460)	(0.075)	(0.138)	(0.013)	(0.029)
Event 1	0.194***	0.150***	-1.000**	-1.480***	0.190	0.043	0.903***
	(0.048)	(0.043)	(0.366)	(0.050)	(0.535)	(0.040)	(0.172)
Event 2	0.102	0.200***	-1.218***	-1.422***	-0.642	0.046	0.905***
	(0.053)	(0.046)	(0.333)	(0.051)	(1.754)	(0.033)	(0.192)
Event 3	0.105*	0.223***	-1.266***	-1.181***	1.189***	0.054	0.902***
	(0.053)	(0.046)	(0.330)	(0.048)	(0.305)	(0.035)	(0.186)
Event 4	0.145*	0.172***	-1.034**	-1.209***	-0.272	0.065	0.913***
	(0.062)	(0.052)	(0.342)	(0.053)	(0.709)	(0.041)	(0.173)
Event 5	0.179**	0.141*	-1.000**	-0.507***	-1.272	0.045	0.937***
	(0.068)	(0.056)	(0.354)	(0.059)	(0.717)	(0.053)	(0.145)
Event 6	0.106*	0.060	-0.069	-0.823***	-0.896*	0.296***	0.515***
	(0.044)	(0.082)	(0.472)	(0.089)	(0.435)	(0.072)	(0.084)
Event 7	0.090	0.050	-0.105	-0.527***	-0.964*	0.188***	0.710***
	(0.051)	(0.079)	(0.520)	(0.084)	(0.430)	(0.038)	(0.040)
Event 8	0.097*	0.007	-0.255	-1.250***	-1.491*	0.255***	0.515***
	(0.048)	(0.089)	(0.499)	(0.079)	(0.640)	(0.066)	(0.111)
Event 9	0.102*	0.020	-0.713	0.029	0.214	0.058	0.586***
	(0.042)	(0.065)	(0.486)	(0.071)	(0.413)	(0.086)	(0.114)
Event 10	0.120**	-0.006	-0.800*	0.357***	-1.839***	0.109	0.564***
	(0.045)	(0.078)	(0.314)	(0.058)	(0.439)	(0.085)	(0.110)
Event 11	0.119**	0.002	-0.751*	0.208***	-1.736***	0.098	0.588***
	(0.045)	(0.078)	(0.316)	(0.052)	(0.459)	(0.081)	(0.114)
Event 12	0.089	0.045	-0.004	-0.410***	0.287	0.184***	0.749***
	(0.050)	(0.077)	(0.484)	(0.086)	(0.345)	(0.036)	(0.023)
Event 13	0.093	0.044	0.001	-0.301***	0.648	0.190***	0.750***
	(0.049)	(0.076)	(0.482)	(0.088)	(0.344)	(0.036)	(0.022)

Note: The estimated model EGARCH model has the following form: $R_t = a_0 + \sum_{j=1}^{n} b_j R_{t-n} + b_2 S\&P500_t + \varepsilon_t + D_t$ where $\ln(h_t^2) = \omega + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) + \beta \ln(h_{t-1}^2) + D_t$ and where $R_{i,t}$ represents the return on asset i at time t and R_{t-1} represents the first lag of returns r_t. $b_2 S\&P500_t$ represents the return on the S&P500 index and it included as a proxy for market effects. Finally, D_t is included in the variance equation to provide a coefficient relating to the volatility response to the thirty-day period after each identified event.Standard errors are presented in parentheses. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

Table 6: Results of selected EGARCH-methodology based on regulatory announcement affects on IOTA returns

	Mean Eq.			Variance Eq.		
	R_{t-1}	S_t	D_t	D_t	EARCH	EGARCH
All Events	0.221***	0.020	-0.020	-1.022	0.433**	0.561***
	(0.049)	(0.786)	(0.038)	(2.535)	(0.093)	(0.098)
Event 3	0.250***	-0.020	-0.041	-3.837	0.231*	0.631***
	(0.049)	(0.786)	(0.038)	(2.535)	(0.093)	(0.098)
Event 4	0.255***	-0.052	-0.013	-0.062	0.240*	0.620***
	(0.050)	(0.770)	(0.037)	(0.579)	(0.097)	(0.101)
Event 5	0.251***	-0.067	-0.143***	-1.543	0.206*	0.637***
	(0.049)	(0.819)	(0.040)	(1.335)	(0.086)	(0.099)
Event 6	0.245***	-0.052	-0.026	-0.574	0.254*	0.585***
	(0.051)	(0.807)	(0.039)	(0.474)	(0.104)	(0.111)
Event 7	0.246***	-0.068	-0.006	-0.327	0.268*	0.571***
	(0.050)	(0.782)	(0.038)	(0.512)	(0.107)	(0.109)
Event 8	0.211***	-0.146	-0.032	2.460***	0.001	0.804***
	(0.050)	(0.600)	(0.031)	(0.209)	(0.030)	(0.052)
Event 9	0.138	-0.158	0.066	1.004**	0.024	0.666***
	(0.076)	(0.486)	(0.024)	(0.347)	(0.134)	(0.150)
Event 10	0.154	0.030	-0.118***	-1.466*	0.073	0.641***
	(0.079)	(0.303)	(0.017)	(0.740)	(0.140)	(0.146)
Event 11	0.171*	-0.010	-0.075***	-1.578**	0.011	0.633***
	(0.077)	(0.291)	(0.016)	(0.611)	(0.130)	(0.143)
Event 12	0.171*	-0.006	-0.077***	-1.781**	0.062	0.589***
	(0.079)	(0.252)	(0.015)	(0.581)	(0.145)	(0.137)
Event 13	0.276***	0.067	-0.138***	-2.678***	0.111	0.521***
	(0.061)	(0.137)	(0.010)	(0.500)	(0.076)	(0.121)

Note: The estimated model EGARCH model has the following form: $R_t = a_0 + \sum_{j=1}^{n} b_j R_{t-n} + b_2 S\&P500_t + \varepsilon_t + D_t$ where $\ln(h_t^2) = \omega + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) + \beta \ln(h_{t-1}^2) + D_t$ and where $R_{i,t}$ represents the return on asset i at time t and R_{t-1} represents the first lag of returns r_t. $b_2 S\&P500_t$ represents the return on the S&P500 index and it included as a proxy for market effects. Finally, D_t is included in the variance equation to provide a coefficient relating to the volatility response to the thirty-day period after each identified event.Standard errors are presented in parentheses. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

Table 7: Results of selected EGARCH-methodology based on regulatory announcement affects on Nano returns

	Mean Eq.			Variance Eq.		
	R_{t-1}	R_{t-2}	D_t	D_t	EARCH	EGARCH
All Events	0.097	0.134**	-1.313***	0.312	0.019***	0.948***
	(0.058)	(0.047)	(0.108)	(0.289)	(0.004)	(0.162)
Event 4	0.090	0.140***	-1.160***	1.361***	0.042	0.820***
	(0.060)	(0.038)	(0.113)	(0.215)	(0.033)	(0.122)
Event 5	0.128	0.267***	-0.392***	-0.497	0.151	0.749***
	(0.087)	(0.072)	(0.112)	(0.354)	(0.133)	(0.153)
Event 6	0.128	0.267***	-0.222***	-0.581	0.157	0.729***
	(0.087)	(0.074)	(0.113)	(0.398)	(0.141)	(0.156)
Event 7	0.093	0.133**	-1.375***	0.404*	0.004	0.902***
	(0.058)	(0.049)	(0.106)	(0.203)	(0.041)	(0.166)
Event 8	0.128	0.272***	-2.643***	-0.232	0.158	0.778***
	(0.087)	(0.072)	(0.109)	(0.244)	(0.129)	(0.156)
Event 9	0.096	0.150**	-1.246***	0.926*	0.001	0.908***
	(0.059)	(0.049)	(0.107)	(0.421)	(0.055)	(0.160)
Event 10	0.123	0.261***	-2.732***	-1.400*	0.120	0.848***
	(0.083)	(0.067)	(0.094)	(0.708)	(0.111)	(0.161)
Event 11	0.126	0.261***	-2.644***	-1.033	0.128	0.864***
	(0.084)	(0.068)	(0.093)	(0.673)	(0.121)	(0.165)
Event 12	0.133	0.261***	-2.671***	-0.884	0.108	0.836***
	(0.081)	(0.065)	(0.093)	(0.656)	(0.115)	(0.166)
Event 13	0.121	0.256***	-1.109***	-1.705	0.128	0.852***
	(0.084)	(0.067)	(0.082)	(1.125)	(0.114)	(0.161)

Note: The estimated model EGARCH model has the following form: $R_t = a_0 + \sum_{j=1}^{n} b_j R_{t-n} + b_2 S\&P500_t + \varepsilon_t + D_t$ where $\ln(h_t^2) = \omega + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) + \beta \ln(h_{t-1}^2) + D_t$ and where $R_{i,t}$ represents the return on asset i at time t and R_{t-1} represents the first lag of returns r_t. $b_2 S\&P500_t$ represents the return on the S&P500 index and it included as a proxy for market effects. Finally, D_t is included in the variance equation to provide a coefficient relating to the volatility response to the thirty-day period after each identified event.Standard errors are presented in parentheses. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

Table 8: Results of selected EGARCH-methodology based on regulatory announcement affects on Obyte (formerly Byteball) returns

	Mean Eq.				Variance Eq.		
	R_{t-1}	R_{t-2}	S_t	D_t	D_t	EARCH	EGARCH
All Events	0.213**	0.148	-0.454	-0.218***	-2.521**	0.046***	0.918***
	(0.067)	(0.081)	(0.846)	(0.042)	(0.768)	(0.010)	(0.011)
Event 1	0.184**	0.138*	-0.089	-0.089	1.669***	0.002	0.944***
	(0.060)	(0.066)	(0.967)	(0.045)	(0.201)	(0.007)	(0.020)
Event 2	0.153**	0.098*	-0.312	-0.242***	-0.427	0.010	0.341
	(0.057)	(0.042)	(0.965)	(0.044)	(0.276)	(0.025)	(0.889)
Event 3	0.162**	0.093*	-0.264	-0.186***	-1.120	0.015	0.687**
	(0.055)	(0.040)	(0.920)	(0.042)	(0.578)	(0.020)	(0.232)
Event 4	0.165**	0.104*	0.098	0.190***	-0.129	0.014	0.406
	(0.054)	(0.045)	(0.991)	(0.045)	(0.114)	(0.023)	(0.389)
Event 5	0.153**	0.126	-0.318	-0.106**	-2.280***	-0.002	0.793***
	(0.057)	(0.064)	(1.004)	(0.047)	(0.387)	(0.018)	(0.146)
Event 6	0.159**	0.113*	-0.107	-0.025	-1.878***	-0.014	-0.082
	(0.058)	(0.048)	(1.025)	(0.047)	(0.387)	(0.027)	(0.219)
Event 7	0.145*	0.099*	-0.188	-0.118***	-1.451***	-0.016	0.131
	(0.059)	(0.042)	(0.198)	(0.012)	(0.434)	(0.024)	(0.263)
Event 8	0.148*	0.102	-0.368	-0.186***	-1.046*	-0.004	0.742*
	(0.059)	(0.066)	(0.988)	(0.046)	(0.413)	(0.017)	(0.317)
Event 9	0.155**	0.146**	-0.589	-0.553***	1.345***	-0.016	0.619***
	(0.055)	(0.051)	(1.163)	(0.053)	(0.134)	(0.021)	(0.119)
Event 10	0.196***	0.119*	-0.108	-0.108***	-0.019	-0.014	0.499***
	(0.056)	(0.055)	(0.108)	(0.009)	(0.107)	(0.018)	(0.129)
Event 11	0.155**	0.104	-0.660	-0.511***	-1.394**	0.017	0.145
	(0.057)	(0.067)	(0.857)	(0.042)	(0.454)	(0.038)	(1.341)
Event 12	0.176*	0.093	-0.618	-0.459***	-1.187*	0.064	0.202
	(0.077)	(0.059)	(0.893)	(0.042)	(0.477)	(0.050)	(0.293)
Event 13	0.164**	0.091	-0.738	-0.597***	-1.749***	0.014	0.499
	(0.057)	(0.067)	(0.681)	(0.034)	(0.465)	(0.035)	(1.287)

Note: The estimated model EGARCH model has the following form: $R_t = a_0 + \sum_{j=1}^{n} b_j R_{t-n} + b_2 S\&P500_t + \varepsilon_t + D_t$ where $\ln(h_t^2) = \omega + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) + \beta \ln(h_{t-1}^2) + D_t$ and where $R_{i,t}$ represents the return on asset i at time t and R_{t-1} represents the first lag of returns r_t. $b_2 S\&P500_t$ represents the return on the S&P500 index and it included as a proxy for market effects. Finally, D_t is included in the variance equation to provide a coefficient relating to the volatility response to the thirty-day period after each identified event.Standard errors are presented in parentheses. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

Table 9: Results of selected EGARCH-methodology based on regulatory announcement affects on Verge returns

	Mean Eq.					Variance Eq.		
	R_{t-1}	R_{t-2}	R_{t-3}	S_t	D_t	D_t	EARCH	EGARCH
All Events	0.211***	0.055	0.198**	0.082	-0.829***	-3.244***	0.056***	0.862***
	(0.046)	(0.060)	(0.062)	(0.826)	(0.106)	(0.307)	(0.013)	(0.009)
Event 1	0.245***	0.077	0.261**	0.676	-1.692***	2.750***	0.057***	0.872***
	(0.053)	(0.090)	(0.088)	(1.213)	(0.151)	(0.539)	(0.024)	(0.011)
Event 2	0.429***	0.104*	0.044	-0.213	-1.248***	-0.396	0.021	0.820***
	(0.024)	(0.046)	(0.053)	(1.263)	(0.145)	(0.779)	(0.017)	(0.235)
Event 3	0.437***	0.098*	0.028	-0.581	-1.021***	-1.504	0.019	0.935***
	(0.024)	(0.043)	(0.052)	(1.061)	(0.127)	(1.185)	(0.015)	(0.239)
Event 4	0.242***	0.080	0.255**	0.723	-1.582***	0.117	0.070***	0.869***
	(0.052)	(0.093)	(0.088)	(1.264)	(0.162)	(0.527)	(0.026)	(0.013)
Event 5	0.065**	0.128**	0.093*	-1.110	2.238***	-3.158***	-0.007	0.282***
	(0.021)	(0.046)	(0.039)	(1.287)	(0.136)	(0.823)	(0.014)	(0.178)
Event 6	0.253***	0.185***	-0.060*	-1.554	1.953***	-1.557*	0.064*	0.479***
	(0.041)	(0.019)	(0.030)	(0.807)	(0.098)	(0.618)	(0.028)	(0.228)
Event 7	0.245***	0.183***	-0.065*	-1.599*	0.547***	-0.856	0.058*	0.639***
	(0.038)	(0.018)	(0.029)	(0.765)	(0.094)	(0.678)	(0.026)	(0.236)
Event 8	0.245***	0.181***	-0.065*	-1.701*	0.485***	-2.014	0.054*	0.736***
	(0.037)	(0.017)	(0.029)	(0.714)	(0.088)	(2.016)	(0.024)	(0.241)
Event 9	0.246***	0.077	0.226**	0.509	-0.901***	3.305***	0.072***	0.869***
	(0.051)	(0.088)	(0.082)	(1.149)	(0.147)	(0.750)	(0.025)	(0.011)
Event 10	0.051*	0.112	0.113**	-0.539	0.568***	-2.977***	0.017	0.873***
	(0.020)	(0.083)	(0.043)	(0.908)	(0.099)	(0.757)	(0.025)	(0.146)
Event 11	0.279***	0.124	0.307***	0.094	-1.060***	-0.442***	0.017	0.845***
	(0.066)	(0.070)	(0.059)	(0.593)	(0.087)	(0.072)	(0.025)	(0.016)
Event 12	0.244***	0.205***	-0.067*	-0.424	-0.067	-1.660*	0.084**	0.472***
	(0.042)	(0.019)	(0.029)	(0.490)	(0.065)	(0.829)	(0.030)	(0.223)
Event 13	0.240***	0.177***	-0.091***	-0.060	-0.500***	-7.495	0.043*	0.201***
	(0.030)	(0.016)	(0.025)	(0.255)	(0.037)	(1.491)	(0.018)	(0.259)

Note: The estimated model EGARCH model has the following form: $R_t = a_0 + \sum_{j=1}^{n} b_j R_{t-n} + b_2 S\&P500_t + \varepsilon_t + D_t$ where $\ln(h_t^2) = \omega + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) + \beta \ln(h_{t-1}^2) + D_t$ and where $R_{i,t}$ represents the return on asset i at time t and R_{t-1} represents the first lag of returns r_t. $b_2 S\&P500_t$ represents the return on the S&P500 index and it included as a proxy for market effects. Finally, D_t is included in the variance equation to provide a coefficient relating to the volatility response to the thirty-day period after each identified event.Standard errors are presented in parentheses. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

Table 10: Results of selected EGARCH-methodology based on regulatory announcement affects on Qtum returns

	Mean Eq.			Variance Eq.		
	R_{t-1}	S_t	D_t	D_t	EARCH	EGARCH
All Events	0.289**	-0.595	-0.436***	0.683	0.152*	0.582***
	(0.095)	(1.168)	(0.096)	(0.378)	(0.059)	(0.098)
Event 3	0.286**	-0.481	-0.116	1.280***	0.193	0.449*
	(0.109)	(1.112)	(0.094)	(0.229)	(0.116)	(0.206)
Event 4	0.302***	-0.457	-0.220	0.106	0.089***	0.860***
	(0.082)	(1.019)	(0.086)	(0.471)	(0.023)	(0.024)
Event 5	0.296***	-0.391	-0.159	-1.114	0.083***	0.868***
	(0.081)	(1.111)	(0.091)	(1.032)	(0.021)	(0.023)
Event 6	0.288***	-0.422	-0.181	-3.839	0.072***	0.880***
	(0.077)	(1.115)	(0.092)	(1.954)	(0.017)	(0.021)
Event 7	0.381***	-0.322	-0.177	-3.338***	0.078***	0.861***
	(0.069)	(0.875)	(0.079)	(1.157)	(0.012)	(0.015)
Event 8	0.269**	-0.096	-0.457***	-2.363***	0.142*	0.554***
	(0.097)	(0.988)	(0.078)	(0.565)	(0.063)	(0.145)
Event 9	0.376***	-0.113	-0.074	3.845***	0.180***	0.780***
	(0.072)	(0.636)	(0.055)	(0.558)	(0.044)	(0.031)
Event 10	0.282**	-0.349	0.108	-0.890***	0.159*	0.449*
	(0.102)	(0.922)	(0.080)	(0.266)	(0.078)	(0.191)
Event 11	0.286**	-0.403	0.184*	-0.893**	0.144*	0.518**
	(0.098)	(0.900)	(0.078)	(0.286)	(0.065)	(0.170)
Event 12	0.341***	-0.452	0.019	-2.851***	0.317	0.268
	(0.102)	(0.380)	(0.035)	(0.674)	(0.166)	(0.225)
Event 13	0.324***	-0.049	0.024	-5.182***	-0.005	0.726***
	(0.037)	(0.702)	(0.049)	(0.548)	(0.011)	(0.112)

Note: The estimated model EGARCH model has the following form: $R_t = a_0 + \sum_{j=1}^{n} b_j R_{t-n} + b_2 S\&P500_t + \varepsilon_t + D_t$ where $\ln(h_t^2) = \omega + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) + \beta \ln(h_{t-1}^2) + D_t$ and where $R_{i,t}$ represents the return on asset i at time t and R_{t-1} represents the first lag of returns r_t. $b_2 S\&P500_t$ represents the return on the S&P500 index and it included as a proxy for market effects. Finally, D_t is included in the variance equation to provide a coefficient relating to the volatility response to the thirty-day period after each identified event.Standard errors are presented in parentheses. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.

Table 11: Results of selected EGARCH-methodology based on regulatory announcement affects on Factom returns

	Mean Equation			Variance Eq.		
	R_{t-1}	S_t	D_t	D_t	EARCH	EGARCH
All Events	0.192**	-0.628	-0.676***	-1.667***	0.044*	0.905***
	(0.059)	(0.371)	(0.021)	(0.377)	(0.018)	(0.027)
Event 1	0.197***	-0.738	-0.800***	0.434	0.170**	0.585***
	(0.041)	(0.462)	(0.025)	(0.222)	(0.066)	(0.128)
Event 2	0.195***	-0.662	-0.722***	-0.613	0.113	0.598***
	(0.043)	(0.448)	(0.024)	(0.390)	(0.061)	(0.173)
Event 3	0.202***	-0.755	-0.809***	0.654***	-0.021	0.803***
	(0.052)	(0.444)	(0.023)	(0.160)	(0.018)	(0.121)
Event 4	0.203***	-0.719	-0.788***	0.201	0.111	0.607***
	(0.042)	(0.466)	(0.025)	(0.299)	(0.062)	(0.177)
Event 5	0.206**	-0.875	-0.924***	-1.835***	0.024	0.055
	(0.067)	(0.469)	(0.024)	(0.385)	(0.025)	(1.292)
Event 6	0.215***	-0.685	-0.685***	-1.754***	0.027	-0.104
	(0.065)	(0.455)	(0.057)	(0.354)	(0.028)	(0.950)
Event 7	0.205**	-0.789	-0.833***	-1.395**	0.025	-0.205
	(0.067)	(0.466)	(0.024)	(0.435)	(0.025)	(1.028)
Event 8	0.202***	-0.931*	-0.076***	0.810**	-0.007	0.927***
	(0.045)	(0.467)	(0.024)	(0.253)	(0.007)	(0.074)
Event 9	0.177**	-0.915*	-0.079***	0.886***	0.034	0.163
	(0.066)	(0.450)	(0.023)	(0.184)	(0.026)	(0.931)
Event 10	0.206***	-0.629	-0.698***	-0.786	0.068	0.669**
	(0.044)	(0.405)	(0.022)	(0.753)	(0.049)	(0.215)
Event 11	0.211***	-0.628	-0.696***	-0.947	0.060	0.684**
	(0.044)	(0.392)	(0.021)	(0.884)	(0.046)	(0.220)
Event 12	0.217***	-0.658	-0.719***	-0.964	0.032	0.365
	(0.064)	(0.385)	(0.021)	(0.632)	(0.029)	(0.781)
Event 13	0.235***	-0.917*	-0.065***	-0.628*	0.028***	0.992***
	(0.052)	(0.389)	(0.020)	(0.266)	(0.005)	(0.005)

Note: The estimated model EGARCH model has the following form: $R_t = a_0 + \sum_{j=1}^{n} b_j R_{t-n} + b_2 S\&P500_t + \varepsilon_t + D_t$ where $\ln(h_t^2) = \omega + \alpha\varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|)) + \beta \ln(h_{t-1}^2) + D_t$ and where $R_{i,t}$ represents the return on asset i at time t and R_{t-1} represents the first lag of returns r_t. $b_2 S\&P500_t$ represents the return on the S&P500 index and it included as a proxy for market effects. Finally, D_t is included in the variance equation to provide a coefficient relating to the volatility response to the thirty-day period after each identified event.Standard errors are presented in parentheses. ***, ** and * represent significance at the 1%, 5% and 10% level respectively.