**Ph.D. 2020**

# ESSAYS IN ALTERNATIVE MONEY, BANKING, FINANCE

## The monetary & financial nature of cryptocurrencies in distributed ledgers

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# Essays In Alternative Money, Banking, Finance

*The monetary & financial nature of cryptocurrencies in distributed ledgers*

by
Dimitrios M. Koutsoupakis

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A THESIS SUBMITTED TO THE
DEPARTMENT OF ECONOMICS OF THE
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# Alternative thesis format

This thesis is in alternative format and includes the following papers:

[1] Koutsoupakis, D. (2020). Varieties of Distributed Ledgers. A ten-year commemoration.

[2] Koutsoupakis, D. (2020). A survey of the Distributed Ledgers literature. A ten-year commemoration.

[3] Koutsoupakis, D. (2020). An inquiry into cryptocurrencies as Alternative Banking.

[4] Koutsoupakis, D. (2020). Are Stable cryptocurrencies exempted from Impossible Trinity?

[5] Koutsoupakis, D. (2020). Innovation Finance beyond Bitcoin: Cryptocurrencies as Alternative Investments. In *Recent Advances and Applications in Alternative Investments* (pp. 220-258). IGI Global.

[6] Koutsoupakis, D. (2020). On the Weak Form Efficiency within and across cryptocurrency market indexes.



Dimitrios Koutsoupakis
23rd May, 2020

# Abstract

This PhD thesis is motivated by the unprecedented monetary and financial nature of cryptocurrencies issued and circulated in Distributed Ledgers for that it has not been collectively studied. Distributed ledgers can be viewed as payment networks operating without intermediary for exchanging wealth wherein two roles are assumed. More specifically, that of clearing house (in settling transactions) and that of regulator (for controlling the supply). Aside from the former service which is commonplace in money issuance industry's ordinary business of life, there is something unusual that stems from the latter that is, the system itself creates its own *numéraire* referred to as cryptocurrency. Such alternative systems at least outwardly challenge and as though may supplant the established today's banking and finance paradigm which is traditionally associated with (a) currencies (sovereign money) and (b) securities (either in the form of debt or equity). Interestingly, the latter, so far, are only expressed in the unit of account of the former. In the foreign exchange market, the supply of currencies is linked to the activities of commercial banking which are monitored by national and international monetary authorities. To that extent, cryptocurrencies can offer a wide variety of alternatives that were not previously available to private entities and the general public when it comes to designing investment assets, credit instruments and, of course, cash. Traditionally, these have been provided by institutions such as centralized exchanges, accredited banks by a central bank and the State.

The first two chapters broadly examine the relevance of the newly established Distributed Ledgers ecosystems as well as the impact on the economic literature through ages.

Chapter 1 first endeavors to collect and describe the varieties of Distributed Ledgers spanned throughout the first ten years following the inception of Bitcoin, yet from a critical perspective aiming to mark not only the dissimilarity with traditional monetary and financial assets but also growth potential. This allows to better grasp the diversity within the market as all cryptocurrencies are not alike rather are created to serve different causes. Other pure financial (to fund a project in the form of a pre-payment), other pure monetary (to reward benevolent economic behavior, settle transaction cheaper than traditional banking systems or/and ensure stable purchasing power of a bundle of goods) and other a combination of the two. Cryptocurrencies only live in distributed ledgers and can be broadly distinguished between Algorithmic (if decentralized) and Token (if centralized, thus IOU). As the cryptocurrency market matures in volume and number of participants, we identified the need for a taxonomy able to classify the constant diffusion

of wide-ranging cryptocurrencies into standard categorical asset classes on the basis of the criteria of liability, convertibility of collateral and revenue recognition which we embed. This is suited to formulate distinct accounting standards and tax policies of Initial Coin and Token Offerings.

Chapter 2 contributes an all-encompassing survey of literature on this still uncharted breed of research looming anew. A critical approach is employed in reviewing all related works on blockchain and cryptocurrencies research through ages. The main contribution is filling the evident shortage of a literature review able to collectively record the chain of evolution of research on distributed ledgers, cryptocurrencies and blockchain. The inherent scope is to point out that this new research field embraces economic literature across all its main branches, thus not limited to financial economics in examining a new (alternative) asset market. To do so, we further contribute by identifying the four alternative perspectives that blockchain and cryptocurrencies blueprints have introduced and in turn, effectively challenge industry and literature for that they deliver new frameworks of (i) auctioneer (in clearing), (ii) organization (in governance), (iii) money (in exchange) and (iv) capital (in raising financing) which have been traditionally linked to the necessity of centralization.

The next two chapters probe into the monetary nature of cryptocurrencies. The motivation is to show why and how cryptocurrencies could play a significant role as a substitute to traditional banking.

Chapter 3 contributes a conceptual monetary analysis of cryptocurrencies. Our approach differs from all previous attempts by introducing all kinds of cryptocurrencies to the theory and practice of money and currency exchange rate arrangements. At the beginning, we attempt to position cryptocurrencies in the theory and concepts of money and banking. This work will have the effect of bringing cryptocurrencies as closely as possible to the definitions and operations of central and commercial banking. By mastering all varieties of cryptocurrencies (algorithmic, tokens, stablecoins) with respect to their monetary foundations, we envisage how competition with traditional banking in the money markets is likely to occur. Note that as monetary assets, cryptocurrencies are closer to *currency*, thus cash items rather to bank checking accounts, thus cash equivalent items for that the peer-to-peer (distributed) nature of the blockchain renders cryptocurrencies' issuance irreversible. Though, cryptocurrencies look alike bank deposits for that their electronic nature allow geographically distant trades as opposed to *currency*. We conclude that (a) Token cryptocurrencies under quantity rules by meeting the deferred payments function can introduce competition to commercial banking's checking accounts and pledged asset (short-term) lines of credit and (b) Stable cryptocurrencies by meeting the media of exchange function can introduce competition to commercial banking's deposits alike e-money issuance institutions. Finally, (c) Algorithmic cryptocurrencies under quantity rules such as Bitcoin pertain investment nature whose intrinsic value stems from the usage of these coins in the decentralized built-in blockchain. These may be perceived as alternative commodities of digital nature chiefly demanded to store value. Notably, traditional currencies are still of the greatest value and importance to the real economy and surprisingly to cryptocurrency ecosystems as well for that they convey the intelligence of the prevailing numéraire. The absence of inside money, however, due to lack of portfolio management activities impedes cryptocurrencies' penetration into capital markets where the banking sector continues to prevail. In addition, we demonstrate the existing pluralism in cryptocurrency asset classes by showing all different trajectories of supply and demand functions in these markets.

Chapter 4 focuses on Stablecoins. We set up a sample of 4 representative cryptocurrencies corresponding to the main categorical cases of Stablecoins. This work contributes fresh insights with respect to their diverse monetary structures which adhere to fixed exchange rate regimes. We provide an empirical framework analogous to Impossible Trinity for exploring monetary arrangements across Stablecoins wherein reserves are held. While the hypothesis is supported for all cryptocurrencies in question, the trade-off combination among exchange rate stability, capital openness and monetary independence varies with the categorical types of Stablecoins. This uncovers the inherent constraints of their monetary structures compared to the rest genres of cryptocurrencies. This is the first work in this attempt for that the literature, so far, only focuses on empirically investigating the presence of financial theories in cryptocurrencies.

The last two chapters delve into the financial nature of cryptocurrencies. The motivation is to infer trading behavior by showing recent developments in investment practice in constructing cryptocurrency portfolios while highlighting the role of grouping cryptocurrencies into asset classes and indexes for comparing and forecasting performance more evenly.

Chapter 5 introduces cryptocurrencies to investment theory and practice. We first look at the different risk-return profiles of each asset class market leader and then construct various mean-variance portfolios to only include cryptocurrencies or blend these with traditional investment assets such as equities and currencies as well other such as commodities using a dataset of 6 cryptocurrencies and 10 ths. observations. The results are compatible with the literature highlighting the effect of reducing non-systemic risk.

Chapter 6 contributes empirical evidence of market efficiency of cryptocurrency markets. We focus on examining trading behavior within and across cryptocurrency indexes which we set up. This work contributes to a growing literature which calls for constructing crypto market indexes. The study of peer groups and indexes is important for matching investors' tastes and preferences. The motivation is to identify similarities and differences in trading activity both across and within these composite indexes. We build indexes of daily returns using market capitalization data but useful extensions may include other variations. For assets, we use the daily change in prices (exchange rates). We use daily data frequency of 57 cryptocurrencies throughout their entire trading history corresponding to approximately 100 ths. observations, aiming to draw inferences about the weak form efficiency hypothesis, yet conditional on the varieties of crypto-asset classes (indexes). Against this background, we investigate stylized facts traditionally found in daily returns, by employing tests for the presence of random walks, white noise as well as tests for effects namely symmetric time-varying, risk premium, leverage, calendar and regime switching. The results support the existence of switch of states (high-low volatility, from negative to positive returns) while do not support the existence of calendar effects on Monday. With regards to the market cap indexes, most exhibit positive in-excess returns going towards the end of the week and especially on Friday and during the Weekend. The less likely anomaly this study can support is the existence of leverage effects.

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# Prelude

And, the gracious prophet foretold, not long ago the advent of non-physical and non-governmental currency:

> *I think that the Internet is going to be one of the major forces for reducing the role of government. One thing that's missing but will soon be developed is a reliable e-cash, a method whereby on the Internet you can transfer funds from A to B without A knowing B or B knowing A. The way I can take a $20 bill hand it over to you and then there's no record of where it came from. You may get that without knowing who I am. That kind of thing will develop on the Internet...*
> **- Nobel Laureate Milton Friedman in a 1999 TV interview**

And, on the last day of October of the year 2008 the revelation arrived with the most unorthodox style of concealment. That day, at 18:10 GMT an unsolicited and unidentified mail with the subject line *"Bitcoin P2P e-cash paper"* appeared on a cryptography mailing list. The electronic address *satoshi@vistomail.com* was shown as the mail sender. In the main body of the mail there was a laconic and non-personalized message saying:

> *I've been working on a new electronic cash system that's fully peer-to-peer, with no trusted third party. The paper is available at:*
> *http://www.bitcoin.org/bitcoin.pdf*

Formatted in standard academic style, the paper was barely nine pages long including eight references, seven figures and a few lines of code. The title was *"Bitcoin: A Peer-to-Peer Electronic Cash System"* and the complete name of the author was Satoshi Nakamoto. In his technical paper from the computer science viewpoint, Satoshi Nakamoto devotes a paragraph to explain the economics rationale and subtly to confess his political motivation. In his own words:

> *The root problem with conventional currency is all the trust that's required to make it work. The central bank must be trusted not to debase the currency, but the history of fiat currencies is full of breaches of that trust. Banks must be trusted to hold our money and transfer it electronically, but they lend it out in waves of credit bubbles with barely a fraction in reserve.*

In the next couple of months, some programmers were intrigued by the Bitcoin paper and decide to set up a peer-to-peer (p2p) forum to further discuss it. In the end, and with the active collaboration of Satoshi Nakamoto the p2p community developed Bitcoin v0.1 which was uploaded as open-source software on the internet on January 9, 2009. Until today the inventor of the Bitcoin protocol remains anonymous for that the name Satoshi Nakamoto is fictitious. Put it plainly, the identity of the person(s) whose nine-page work spawned a USD 708 bil cryptocurrency market (total market capitalization on January 7, 2018) remains enduring mystery and the stories about Bitcoin's inception resemble a science fiction cinematographic screenplay.

When Bitcoin went online, Satoshi Nakamoto initiated the first ever transaction in the Bitcoin network and he allegedly embedded the following brief line of text into the cryptographic data:

*The Times 03/Jan/2009 Chancellor on brink of second bailout for banks.*[1]

Following the release of Bitcoin, Satoshi Nakamoto continued to participate in online peer-to-peer forums via untraceable emails and websites and work with people on the Bitcoin open-source project, "but took care never to reveal anything personal about himself".[2] At the end of 2010, he "began to fade from the community"[3] for unclear reason. His last known correspondence was on April 23, 2011 when he reportedly said that "I've moved on to other things. It's [the open-source software] in good hands with Gavin [another developer in the community] and everyone".[4] By some extraordinary coincidence, that period the Central Intelligence Agency (CIA) in the United States started questioning people involved with the p2p community forum and were in close contact with Satoshi Nakamoto.[5]

Three years later, on March 7, 2014, one last message appeared on the p2p forum reportedly by Satoshi Nakamoto who then disappeared for good. The message was: "I am not Dorian Nakamoto". At that time, rumors were spreading that the Newsweek magazine was about to issue a controversial 4.500-word cover story claiming that they identified Dorian Prentice (Satoshi) Nakamoto as "the elusive creator of Bitcoin", a 65-year old Japanese-American unemployed engineer living in California (USA). A few days later when the story was published, the latter angrily refuted the allegation. Later, he sued the magazine.

Over the past years, there has been much speculation as to the true identity of Satoshi Nakamoto with suspects including quite a few academics and professionals in the fields of information technology and finance. Strangely, all have repeatedly and

[1]This is direct reference to an article published by *The Times* on Jan, 3 2009. Note that Joshua Davis, an American author published an article on October 10,2011 with the title "The Crypto-Currency. Bitcoin and its mysterious inventor" aiming to build a profile of Satoshi Nakamoto. He claims to be a person "with flawless English, who uses British spelling though in an initial post announcing Bitcoin he employed American-style spelling, his comments tended to appear after normal business hours ended in the United Kingdom and has deep understanding of economics, cryptography, and peer-to-peer networking".

[2]Source: Coindesk, 2016

[3]Source: Coindesk, 2016

[4]Source: Coindesk, 2016

[5]Source: newsbtc, 2016

strongly denied any kind of involvement. In December 2015 allegedly leaked documents supplied to two technology magazines suggested[6] that Craig Steven Wright, a 46 year-old Australian academic and entrepreneur may has been the man behind the mask. Just a few hours later, Wright's house "was raided by Australian Federal investigators".[7] Suspected Bitcoin founder Craig Steven Wright disappeared following the publication of the story without confirming or denying it.[8]

Until 2016, no one had ever claimed to be the creator of Bitcoin. But, on May 2, 2016 Wright publicly admitted to be Satoshi Nakamoto and later disclosed the signature (private key) used in the earliest recorded transaction in the Blockchain history. Gavin Andersen, one of the earliest known developers to have communicated with Satoshi Nakamoto after talking to Wright he blogged "I believe Craig Steven Wright is the person who invented Bitcoin". Two days later he felt compelled to regret backing Wright's claim. Critics said[9] that Wright's proof is unconvincing because he did not provide evidence about the *"genesis block"*, that is the first 50 bitcoins ever created, thus prior to the first Bitcoin transaction.

On May 5, 2016, Wright posted an emotional statement implying that he will not be providing any further proof of his claims. In his own words:

> *I believed that I could put the years of anonymity and hiding behind me (...) I can only say I'm sorry. And goodbye.*

Adding to the intrigue, and to preserve Bitcoin's *Power of the Myth*, one last alleged fact. There are speculations[10] that Satoshi Nakamoto "may have around 1 million bitcoins" from very early mining. At USD 20.000 per bitcoin in late 2017, that corresponded to a wealth approximately USD 20 bil. To date, these specific wallets assumed to belong to Satoshi Nakamoto remain inactive; they have never spent a single bitcoin. This is strange, to say the least.

Remarkably, talking about the Bitcoin paper in late 2008 no one can look back and review step by step the chain of evolution that led to the inception of the first ever cryptocurrency for that there is no related literature whatsoever. What exists is an alleged proximity of Bitcoin with seven irrelevant to each other academic works, at first sight coming from two diverse disciplines, yet related to each other in the most unusual manner. The background of these works lies with cryptography and accountancy.

[6] The magazines were Wired, Gizmodo. Source: Business Insider, 2016

[7] Source: The Guardian, 2016

[8] Source: Siliconangle, 2016

[9] Source BBC news, 2016

[10] An empiric estimation performed by a Bitcoin developer named Sergio Lerner. Source: Business Insider, 2016

The following works span over two decades and is our best case of how the notion of Distributed Ledgers underpinning blockchain and cryptocurrencies was shaped.

[1] In the early 80s, Prof. David Lee Chaum, a computer scientist laid the first stone to electronic cash application with his paper "Blind signatures for untraceable payments".[11] Theferfore, it should be clear that the development of electronic protocols for digital payments and the notion of digital coins did not arrive with Bitcoin. Brito & Castillo (2013) explain that in Chaum we are able to realize for the first time the "double-spending problem"[12] which necessities the existence of a centralized (trusted) third-party.

[2] In the year 1989, Prof Yuji Ijiri, a certified public accountant arguably coined the term triple-entry accounting in a monograph entitled "Momentum accounting and triple-entry bookkeeping". Contrary to double entry bookkeeping where changes in balances are independently made by the transactors, in momentum accounting these arrive from the collective recognition of transactions. For Ijiri et al. (1989), in capital accounts *"the present state of an entity is represented by past transactions"* and from there one can expand on recording and sharing common accounts with external parties.

[3] In the year 1997, Adam Back, a computer scientist, publishes a 1.206 word article on-line called "Hashcash" where he employs a cryptographic proof-of-work (PoW) algorithm using hash functions later also used in Bitcoin. Proof of work is a requirement that expensive computations be performed in order to achieve an outcome. Note that Satoshi Nakamoto has allegedly contacted with Adam Back before publishing the Bitcoin paper.

[4] In the year 1998, Wei Dai, a computer engineer publishes a 1.352 word article on-line entitled "b-money". The similarities with Bitcoin are striking. The author uses three times the phrase *"crypto-anarchy"*, proposes a protocol called "b-money" best described as *"money which is impossible to regulate"* where *"exchange of funds is accomplished by collective bookkeeping"* and *"contracts are enforced through the broadcast and signing of transactions with digital signatures"*.

[11] David Lee Chaum, born in 1955, United States. Relevant works: "Untraceable Electronic Mail, Return Addresses, and Digital Pseudonyms" (1981), "Computer Systems Established, Maintained and Trusted by Mutually Suspicious Groups". (1982), "Blind signatures for untraceable payments. Advances in Cryptology Proceedings of Crypto" (1983).

[12] The existence of only digital data and the inexistence of centralized ledger of accounts allow one party copying the currency in their computer and using (double-spending) it multiple times.

Note that Wei Dai's work is the first to appear under the references section in Nakamoto (2008). As a matter of fact, Wei Dai and Satoshi Nakamoto exchanged the following correspondence in August 2008. The latter sent an email whereby an early draft of the Bitcoin paper is attached and an earlier communication with Adam Back is mentioned.

> *I was very interested to read your b-money page. I'm getting ready to release a paper that expands on your ideas into a complete working system. Adam Back (hashcash.org) noticed the similarities and pointed me to your site. I need to find out the year of publication of your b-money page for the citation in my paper. It'll look like: [1] W. Dai, "b-money," http://www.weidai.com/bmoney.txt, (2006?).*

Then, Wei Dei replied as follows:

> *Hi Satoshi. b-money was announced on the cypherpunks mailing list in 1998. Here's the archived post:*
> *http://cypherpunks.venona.com/date/1998/11/msg00941.html*
> *There are some discussions of it at*
> *http://cypherpunks.venona.com/date/1998/12/msg00194.html.*
> *Thanks for letting me know about your paper. I'll take a look at it and let you know if I have any comments or questions.*

[5] Around 1998: Nick Szambo, a computer scientist, publishes a 972 word article entitled "Bit-gold" on December 27, 2008 (just a few days before Bitcoin uploaded on the internet) beginning in a rather obscure manner: "A long time ago I hit upon the idea of bit gold". There is no exact date about "Bit gold" inception but should be around 1998. The term and concept, however, of "smart contracts" used in today's cryptocurrency ecosystem following the release of Ethereum is attributed to Szambo back to 1994.[13] Again, the similarities of "bit gold" with Bitcoin are surprising:

> *checks the unforgeable chain of title in the bit gold title registry (...) Since bit gold is timestamped, the time created as well as the mathematical difficulty of the work can be automatically proven. From this, it can usually be inferred what the cost of producing during that time period was (...) Unlike fungible atoms of gold, but as with collector's items, a large supply during a given time period will drive down the value of those particular items. In this respect "bit gold" acts more like collector's items than like gold (...) all money mankind has ever used has been insecure in one way or another (...) but the most pernicious of which has probably been inflation. Bit gold may provide us with a money of unprecedented security from these dangers.*

[6] In the year 2004: Hal Finney, a computer scientist suggests the idea of RPoW (Reusable Proofs of Work). His motivation was making proof-of-works reusable

[13] See the work with the title "Smart Contracts: Building Blocks for Digital Markets".

for practical purpose which he names “PoW token” and effectively expands on the earlier concept of “Hashcash”.[14]

[7] In the year 2005 Ian Grigg, a financial cryptography researcher uploads a work-in-progress paper with the title “Triple Entry Accounting”. There are many points of resemblance between this work and Bitcoin, but again no formal affinities. The author proposes *“the usage of accounting into the wider domain of digital cash”*, describes a peculiar triple-entry bookkeeping wherein exists a *“ third shared and dynamic repository akin to the classic double-entry accounting”* and argues the necessity of *“internal money”*, thus unit of account, in such peer-to-peer systems.

A few years later, in the year 2008 the first working prototype of Distributed Ledgers putting together the above pieces came forth. It’s name was Bitcoin.

[14] An alleged fact: Finney was the receiver in the first bitcoin transaction ever completed following the *genesis* of the first blockchain block that released the first 50 bitcoins. The sender was Bitcoin’s creator Satoshi Nakamoto. Finney passed away in 2014.

# Chapter 1

# Varieties of Distributed Ledgers. A ten-year commemoration

The premise of this inquiry lies beyond Bitcoin. We showcase the evolution of Distributed Ledgers ecosystems over the ages spurred by the Bitcoin cryptocurrency & blockchain blueprints back in January 2009 causing traditional & alternative payment systems and assets boarders fade. This paper contributes with a taxonomy able to classify the constant diffusion of wide-ranging cryptocurrencies into standard categorical asset classes. This is suited to formulate accounting rules and regulation of Initial Coin and Token Offerings.

## 1.1 Introduction

This paper is motivated by the rapid evolution of Distributed Ledgers, cryptocurrencies and blockchains since Bitcoin's inception in late 2008 (Nakamoto, 2008). Following its release as open-software in early 2009, Bitcoin, has grown in both its popularity as an asset and its prominence as an innovative peer-to-peer payment system. The latter refers to Bitcoin blueprint's accomplishment to leverage the strengths of its underpinning technology to enhance the development of numerous new financial applications and market designs. Our approach is descriptive focusing on surveying all various types of distributed ledgers. The essential contribution of this work lies in its capacity to critically review all Bitcoin cryptocurrency and blockchain offspring over the last ten years, lay out the differences and, in turn, propose classifications along principal dimensions. With a particular focus on cryptocurrencies as assets, the research question addressed is whether all cryptocurrencies should abide by common tax, accounting and legal frameworks or not. While all of them are akin to institutional role intended to be a digital substitute to the political rights offered by cash, Initial (Coin and Token) Offerings are designed on varied accounting conditions. This paper aims at serving a useful basis for understanding the evolution of this FinTech (financial technology) innovation in order to facilitate the discussion for the enactment of Cryptocurrency Accounting Standards.

The structure of this paper is as follows. The next section cites the related literature. In sections 3 and 4, broad definitions are given followed by the main body of this examination wherein classifications are provided. Section 5 raises policy implications and relevant political economy issues. The last section concludes.

## 1.2 Literature

The literature on Bitcoin commences two years after its launch in 2009. One of the first comprehensive works to systematically review the fundamental perspectives of the underlying Distributed Ledgers technology in Bitcoin is found in Böhme et al. (2015). In true, most studies focus more on the integration of blockchains with the real economy and less on cryptocurrencies. Catalini & Gans (2016) assert that blockchain-based operations are not cost-free highlighting the importance of two cost factors namely the cost of verification and the cost of networking. S. Davidson et al. (2016) introduces this new area of research to the institutional economics literature (efficient institutions, common governance, incomplete contracts, collection action) examining Distributed Ledgers as a new kind of economy rather as a new technological arrival in the economy. A comprehensive research catalague for the proposed applications of the blockchain technology can be found in Risius & Spohrer (2017). Applications include adoption of blockchain verification systems in supply chain management, public notary services, peer-to-peer trading in the renewable energy sector between prosumers, tax registration and much more. Furthermore, Yermack (2017) and Jacobs (2018) have joined this discussion over the replacement of traditional operations in the economy with blockchain-based market designs.

On the other hand, the literature on the potential integration of cryptocurrencies with the real economy apart from Bitcoin is limited. This happens due to lack of the proper understanding of their financial substances. The reason is that the recent advent of centralized cryptocurrencies (which we refer to as Tokens) and stable cryptocurrencies (colloquially called Stablecoins) in the Distributed Ledgers ecosystems have introduced complexity and raised financial and legal inquiries. How does a legal entity record the

Token issuance on its balance sheet? Does it matter if it is an Algorithmic or a Token cryptocurrency? Is there an contractual obligation (IOU)? Interest in classifying the numerous cryptocurrencies issued over the last ten years is shown by Ankenbrand & Bieri (2018) who proposes asset classes on the basis of investment criteria. Today, most cryptocurrencies are projects initiated by start-ups for the financing of their ventures directly from potential (future) users. This new practice has crowded out crowd-funding. The financial innovation brought after Bitcoin which is referred to as Initial Offerings, thus the raise of funds (in cryptocurrencies say in bitcoins) for the sale (offering) of originator's cryptocurrency via an automated process executed by a blockchain smart contract has been criticized. Hacker (2019) argues that these schemes are prone to fraudulent activities.

## 1.3 Innovation economy in Bitcoin

This sections briefly explains the foundations of the Distributed Ledgers innovation introduced by Bitcoin in 2009.

### 1.3.1 An encounter of (distributed) networking and (ledgers) bookkeeping

The terms "cryptocurrency", "Blockchain" and "Bitcoin" used in literature are ambiguously defined. First and foremost, the "Bitcoin cryptocurrency" and the "Bitcoin Blockchain" and the "Bitcoin network" are completely separate from one another. It is commonplace that "Distributed Ledgers" (DL) is a broader category to cover the breakthrough introduced by Bitcoin. Notably, this has brought together computer networks (which share information) and financial accounts (which record information), thus two systems coming from the next diverse disciplines:

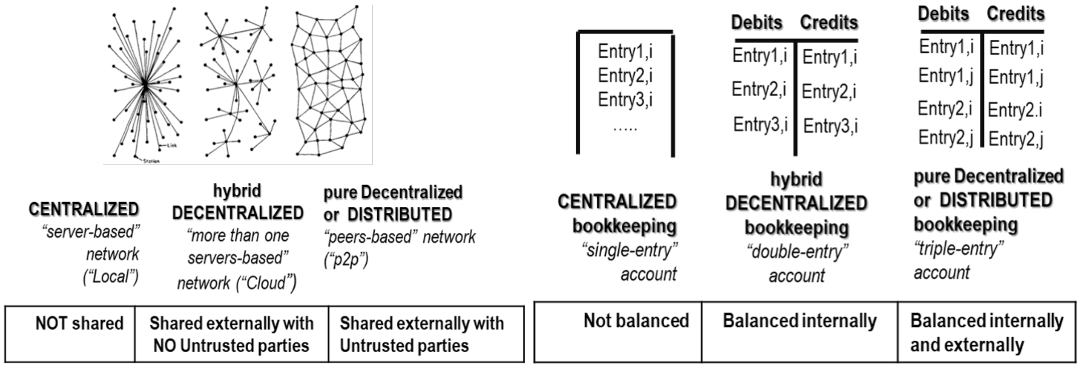
- Distributed (networking of computers) from Computer Sciences
- Ledgers (bookkeeping of accounts) from Economic Sciences

The next figure depicts (a) kinds of computer networks (Baran, 1964) and (b) bookkeeping accounts.[1]

The fundamental concept of peer-to-peer/p2p networking is the partition all operational tasks of the network (community) among all participants (computers) connected

[1]Single-entry accounts date back to the ages of Mesopotamia while double-entry accounting was developed on the eve of 15th c.

Exhibit 1.1: Visualization of networking & bookkeeping




(a) Kinds of computing networks (b) Kinds of bookkeeping accounts

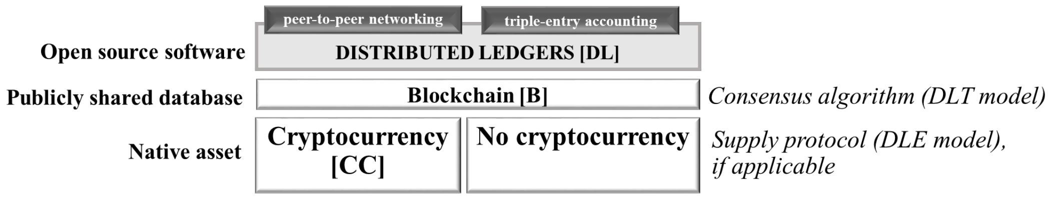
to this network (also called peers or nodes of the network). Therefore it has no single (centralized) point neither of operation and in its aftermath of failure making it uniquely resilient and practically impossible to shut down just like the internet.[2] On the other hand, the fundamental concept of triple entry accounting is recording transactions between agents in a mutually accepted manner (common records of debits and credits in a shared repository). In this context, a further distinction between hybrid and pure decentralization (distributed) is made. While hybrid networks are able to record, transfer and share unique pieces of information (called financial values) among trusted parties similar to today's banking ordinary business life, it was Bitcoin's distributed network that removed the impediment of lack of trust without the need for middlemen. Furthermore, while double-entry accounts balance via debits and credits transaction entries (1 to n) though only internally (say for an entity i), it was Bitcoin's triple-entry ledger that removed the impediment of clearing transactions and agreeing on account balances among internal and external entities (say i and j) without the need for middlemen.

In a nutshell, this breakthrough enables finite units separated in as many decimals is desired (a) to be created and (b) atomically (thus without an intermediary) circulate though not copied (thus, double-spending resistant) between different accounts (balances). This happens in accordance with a pre-defined set of rules (via an algorithm) and regulation (via a supply protocol) written down in a self-executed contractual computer state (referred to as smart contract) whereby both (a) and (b) operations are

[2] As a matter of fact, Hileman & Rauchs (2017) underscore that the Bitcoin network being the largest computer network in human history and still growing has not been down for a single nanosecond in its entire history.

performed by the participants' contributions to the network (computing power). In a practical sense, Distributed Ledger refers to a software connecting via the internet distant computers in a p2p network whereby a database (called Blockchain) of accounts expressed in a distinct unit of account (called cryptocurrency) is publicly shared, updated and synchronized in a transparent and most importantly immutable manner.

Exhibit 1.2: Definitions




The mandatory element is the notion of the public ledger. This leads us to a critical first point. Any cryptocurrency ledger of transactions that is not publicly accessible at least with read-permission falls outside the scope of Distributed Ledgers. Note that write-permissions which refer to granting the right to peers to validate transactions on the ledger can be either public like in Bitcoin or by invitation. These comments are made to clarify that Central Banks Digital Currencies (CBDC) recently proposed in literature (Barrdear & Kumhof, 2016) or similar digital assets issued by sovereign institutions, even though they borrow ideas and applications from Distributed Ledgers cannot not be regarded cryptocurrencies if the blockchain (the database) is implied not to be publicly accessible. Otherwise the blockchain is just another corporate database. There is, moreover, a second point which results from the previous. A cryptocurrency cannot exist without a blockchain though a blockchain can exist without a cryptocurrency.[3]

All the same, such DL projects precondition the next two elements which are elaborated in every white-paper.[4]

[A] **A distributed ledgers technology model [DLTech]** whereby the shared database referred to as "blockchain" operates based on a selected "consensus algorithm". The latter is the method which states how the peer-to-peer environment achieves

[3]The latter refers to the case labeled "no cryptocurrency" and relates to non-monetary applications such as using blockchain in voting systems or tracking the manufacturing history of a product in supply chain applications.

[4]Note that the the technical term "white-paper" refers to a short document usually written in a manner that follows academic standards of published papers and brings close professionals and academics from various disciplines. The team aiming to launch a new cryptocurrency documents the functionality of their proposed (a) economy and (b) technology models. The first ever white-paper was the notorious 9-page long by Satoshi Nakamoto.

agreement among distant and unknown peers. In the absence of a central intermediary, these peers are required to perform the necessary operations that lead to transaction verification namely (a) clearing, thus validate the accuracy of transactions and (b) settling, thus exchange the units of account between accounts.[5] In general, blockchain systems should be viewed as alternative (decentralized) payment systems.

[B] **A distributed ledgers economy model [DLEcon]** whereby the "internal numéraire" referred to as "cryptocurrency" operates based on a selected "supply protocol". The latter is the method which states the set of rules that govern the supply of the cryptocurrency and issuance and thereafter. In general, cryptocurrencies should be viewed as alternative monetary assets.

In computer science (i) p2p networks are not new. Neither are (ii) distributed (shared) files nor (iii) consensus protocols (digital signatures using cryptography). Not even (iv) digital payments in the broader sense. But then, if the above elements are not innovative stand-alone how come Bitcoin network is regarded as a remarkable breakthrough? Not far away from the previous point, the element which was missing and brought the previous together was the idea of combining the above concepts in a single implemention as Antonopoulos (2014) points out.

### 1.3.2 Bitcoin: The first Distributed Ledgers blueprint

Innovation comes in many forms and meanings, yet all have a common ground, that is they solve (the ouput) a well defined problem (the input). For if Bitcoin claims this role, one should at least know which puzzle has resolved. Bitcoin's inception is related to a long-lasting puzzle in Computer Science literature called "The Byzantine General's Problem" (BGP). The original puzzle (1975) goes by the name "The two generals problem". It poses the question how two agents (called generals in the paper) can communicate with each other atomically without having someone in between altering the message.[6] This puzzle has been proven to be unsolvable for that even if the initial message from General A to General B goes through, there is no proof to guarantee the acknowledgment message from B back to A.

[5]More practically, these operations verify that (i) the sender of units indeed possessed the amount she sent and (ii) this amount went directly to the intended receiver and no-one else interfered in-between.

[6]See, E. A. Akkoyunlu, K. Ekanadham, and R. V. Huber, "Some Constraints and Trade-offs in the Design of Network Communications" published in 1975.

Later, the puzzle was revisited by Lamport et al. (1982) and effectively renamed BGP.[7] The twist was to assume two types of agents (issuer and receivers) and at least two receivers. So, the puzzle now states how can the general (issuer) and the lieutenants (receivers) reach an asynchronous consensus. It has been shown that a resilient solution exists if and only if the number of dishonest receivers is less than one third (1/3). Put it more formally, $n > 3m$ where n are total agents (also called processes) and m stands for malicious agents (also called faulty processes). This probabilistic solution is originated by the so-called Byzantine fault tolerance (BFT) based consensus algorithms which are defined as the failure tolerance capability of a system against the Byzantine Generals' Problem. As long as the number of dishonest peers proportionally to the total number of peers goes to zero, then agreement over the true state of the message is secured.

Consensus algorithms in distributed systems, however, continued to puzzle many scholars. The concern was that traditional BFT agreement protocols rely either (a) on the existence of low minority of malicious participants (which can be assured if the majority is chosen, thus trusted) or (b) on having a centralized built-in mechanism which determines what to do in the adverse event of Byzantine failures. The main contribution that the Bitcoin paper puts forward is the formulation of a solution in the case of open and not to be trusted environments. The solution to the BGP as Satoshi Nakamoto himself claimed in a email correspondence in 2008 with members of a p2p forum, is in effect provided by the Proof-of-Work (PoW) chain. A competitive process called mining is proposed which is governed by incentive reward mechanisms in enhancing honest participation for validating transactions by anyone on the network. While BFT rely on who you choose to trust, the PoW algorithm rely on who spent resources (worked). This, however, come at the expense of speed and cost as increasing traction renders PoW algorithms slow and energy consuming. Again, notice that in such peer-to-peer environments solutions arrive in probabilistic forms rather in binary like in centralized systems. Appendix A, accumulates these concepts and relates them to varieties of consensus algorithm used in blockchain types.

In the Bitcoin network there is no topology or hierarchy implied whatsoever, thus it is flat on account of the selection of the PoW algorithm. Unknown (not trusted) agents (called nodes) expense computer power in verifying transactions between other unknown nodes and the winner (fastest computer) unlocks the pre-determined supply schedule of the unit of account. In turn, they receive new units of this asset in a fashion called airdropped (a DL term, thus supplied without paid for exchange) by the Bitcoin system.

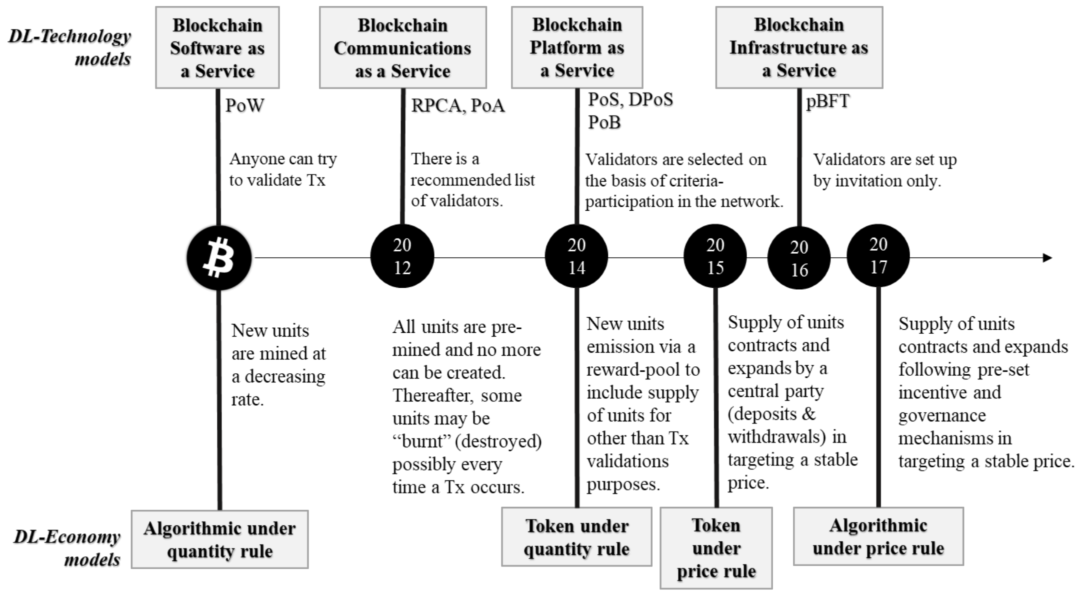
[7] See, Lamport, L., Shostak, R., & Pease, M. (1982). *The Byzantine generals problem. ACM Transactions on Programming Languages and Systems (TOPLAS)*

This supply was modeled to grow at a decreasing rate possibly intended to mimic the supply path of precious metals where at some point in the future these resources are completely extracted from nature. On the other hand, this asset has a well-defined demand for that it is the only one circulating in the blockchain payment system.

## 1.4 The innovation nexus after Bitcoin

The schematic representation of the evolution of the DLTech models (consensus algorithm) and DLEcon models (currency protocol) is illustrated in the next figure. Broadly speaking, these are summarized in four blockchain types and four cryptocurrency types with further segmented categories.

Exhibit 1.3: Innovation nexus after Bitcoin




### 1.4.1 DLTech models & taxonomy of blockchain

It is worthy of elucidating on a taxonomy regarding the various cases of blockchain with respect to two factors namely (a) user-experience (ability to develop applications) and (b) permission to validate transactions. DLTech models segmentation by blockchain type can be done as follows.

- (i) Blockchain Software as a Service (BSaaS) are permission-less with respect to verification of transactions while development of customized applications by users is not possible.

- (ii) Blockchain Platform as a Service (BPaaS) are permission-less with respect to verification while development of customized applications is possible by users for developing smart contracts executed in a peer-to-peer fashion.

- (iii) Blockchain Communications as a Service (BCaaS) are quasi-trusted networks because a third party proposes a list of well-trusted validators though the database is open to anyone. In addition, customized applications are limited mainly in the form of gateways[8].

- (iv) Blockchain Infrastructure as a Service (BIaaS) which are fully-trusted because they require permission with respect to verification. Thus, only by invitation can a node perform operations in this private network.

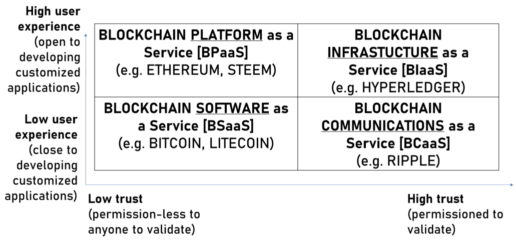
In appendix B, description of the most important consensus algorithms found in Distributed Ledgers is available. The reader should comprehend that the consensus algorithm is first selected on the basis of trust in the network. Not trusted networks which are open to anyone to validate transactions are compelled to use proof-of-work (PoW), proof-of-stake (PoS)[9] and DLTech models alike. More trusted networks use varieties of traditional Practical Byzantine Fault Tolerance algorithms (pBFT) for validation. The PoW algorithm has the drawback of incurring substantial energy consumption as mining competition intensified. PoS and pBFT algorithms resolve this issue at trust expense. This relationship is depicted below.

Abadi & Brunnermeier (2018) argue that blockchains face an impossible trinity, thus simultaneously achieve (i) openness, (ii) correctness (fairness) and (iii) cost-efficiency as each type of consensus algorithm fails to meet one objective (Byzantine Fault Tolerance, Proof-of-Stake and Proof-of-Work respectively). Further discussion on the functionality of the so-called Decentralized Autonomous Organizations (DAO) which can be created on Blockchain Platforms as a Service (BPaaS), from the organization design perspective is offered by Hsieh et al. (2018).

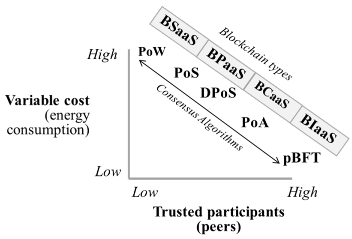
[8] A gateway allows internal (confidential) communication between two parties while the transaction is verified by other nodes. A gateway accepts deposits from users and issues balances into the distributed ledger. Then, gateways redeem these ledger balances against the deposits they hold when units of the unit of account is withdrawn.

[9] The Proof-of-Stake consensus algorithm ask from holders to stake part of their holding prior to participating in validation. If enable in fraudulent transactions, then loose this deposit. Proof-of-Authority (PoA), RPCA and Delegated PoS are variants of the PoS algorithm. Proof-of-Brain (PoB) is used for the development of reward-pool in Altchains.

Exhibit 1.4: Taxonomy of Distributed Ledgers Technology (DLTech) models




(a) Taxonomy of Blockchain




(b) Consensus algorithm types

### 1.4.2 DLEcon models & taxonomy of cryptocurrency

Cryptocurrencies run on their internal built-in blockchain (case of BSaaS, BCaaS and BIaaS) or on external (BPaaS are surrogate blockchain). As far as the former cases are concerned, note that cryptocurrecnies are not shares of ownership or influence of the blockchain. Thus, if someone owns 99 per cent of all available supply of a particular cryptocurrency this does not mean that can change the DLTech model (how consensus occurs) and the DLEcon model (how many new cryptocurrencies pop up). These two are completely detached from the cryptocurrency.

Today, there are have been issued numerous cryptcurrencies (over 5.000), although definitely related to each other with the blockchain used. To throw light upon the varieties, we suggest the next unified framework of crypto-definitions.

**[GENERAL DEFINITIONS A and B]:**

[A] **Decentralized** or **Algorithmic cryptocurrencies** operate on the basis of belief, thus there is no one to assume obligation in accepting this asset as media of exchange for goods. The issuance of Algorithmic cryptocurrencies can be done in two ways. First, through a *genesis block* as in the case of Bitcoin whereby the creator manually shares the first units so as the first transaction can occur. Apparently, a card game cannot start if cards have not been distributed beforehand. Second, via a process called Initial Coin Offering whereby cryptocurrencies are issued in exchange for funds. Following its issuance, these cryptocurrencies are periodically emitted, yet only in accordance with a pre-determined supply schedule.

[B] **Centralized** or **Token cryptocurrencies** operate on the basis of an obligation assumed by the issuer. These assets are aiming to interact either (a) with the real economy, thus paying for products and services billed by legal entities (later these will be named Utility Tokens) or (b) with blockchain-based activities wherein no sale of goods takes place (later these will be named Smart Tokens). Tokens are created either once at issuance in exchange for funds (in a process called Initial Token Offering) or/and periodically emitted at issuer's discretion. It is recommended that cases in which the originator retains important amounts of pre-mined units at escrow accounts should be regarded as centralized cryptocurrencies.[10]

**[SPECIFIC DEFINITIONS 1 and 2]:**

[1] **Supply is in transient state** wherein exchange rate in terms of all other assets floats independently.

[2] **Supply is (targeted to be) in steady state** wherein the exchange rate is targeted at remaining constant with regards to either (i) purchasing power of a bundle of goods (as in Algorithmic Quota and Quota Tokens) or (ii) the price of an anchor (the case of Stable cryptocurrencies explained below).

**[SPECIFIC DEFINITIONS QR and PR]:**

- **Supply adheres to a quantity rule** wherein exchange rate in terms of all other assets floats independently.
- **Supply adheres to a price rule** (colloquially referred to as Stable cryptocurrencies or simply Stablecoins) wherein the exchange rate in terms of an anchor is targeted to be fixed or at least fluctuate within a band.

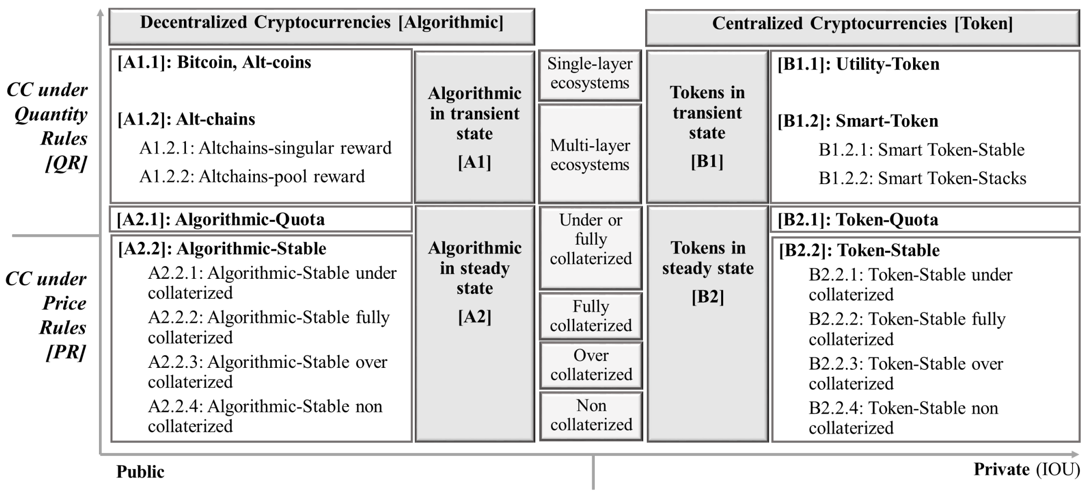
So, any cryptocurrency following its initial release grows in accordance with a predetermined supply path should be classified as decentralized (Algorithmic). In contrast, any cryptocurrency that either (a) had a single Initial Offering and no new units can be created thereafter or (b) after the Initial Offering new units can be created though at the discretion of the issuer should be classified as centralized (Tokens). Arguably, the nature of the former is closer to monetary assets while the latter have add-in financial features for that they suggest the creation of an asset and a liability.

Need to confer a critical note at this point. At an Initial Offering, thus when cryptocurrencies are delivered in exchange for cash or another asset, an expected future benefit is created for that these are pre-payments. For Algorithmic cryptocurrency these Offerings should be closer to the idea of financing a community venture while for Token cryptocurrency these resemble to financing a private venture. Notice that this is neither an equity security nor a debt security rather a peculiar hybrid liability on the

[10] This comment relates to the case of Ripple cryptocurrency.

balance sheet. This is due to the peer-to-peer / distributed nature of the blockchain as cryptocurrencies' issuance is irreversible. For that reason cryptocurrencies have the accounting properties of cash at hand. Recall that at the adverse event of disposal of the asset, re-issuance of securities and bank deposits is possible in compliance with owner's identification procedures. The next table illustrates an extensive version of the proposed taxonomy.

Exhibit 1.5: Taxonomy of Distributed Ledgers Economy (DLEcon) models




According to this taxonomy, the vertical axes depicts the distinction between (i) the quantity rule (or floating exchange rates) and (ii) the price rule (or fixed exchange rates). The horizontal axes shows the distinguish between (a) IOU, thus (private) initiatives associated with an obligation to deliver an output or (b) initiatives which after launch grow in a decentralized community fashion. The former also displays the trade-off between exchange rate stability and non-convertibility. The latter refers to the fact that cryptocurrencies under quantity rules are non-convertible (to another asset) but can be redeemed for paying goods of a private firm (case of Utility Tokens) or for paying on-chain (on the blockchain) fees (case of Bitcoin, Altcoins, Altchains and Smart Tokens) at holder's discretion. Cryptocurrencies under price-rules are convertible to another asset (kept in reserves) for that these are collaterized with the exception of non-collaterized Stablecoins.

Both Algorithmic and Tokens under quantity rules can be uniformly broken down into two categories i.e. single-layer crypto-ecosystems which operate stand-alone and multi-layer crypto-ecosystems which exhibit high interaction with other cryptocurrencies. Single-layer ecosystems are Bitcoin, Altcoins (A11) and Utility Tokens (B11).

Altcoins are alternatives to Bitcoin, thus they are practically clones with minor differences from the economics viewpoint and more significant differences from the technical viewpoint. Multi-layer ecosystems characterized by extroversion to communicate with various applications are Althcains (A12), thus alternatives to the first blockchain introduced by Bitcoin and Smart Tokens (B12). Altchains' innovation was significant for that introduced the development of decentralized applications (dApps) while with Smart Tokens users can access an application.

As far as Altchains classification is concerned, these are further divided into two categories based on the distribution policy of new units. Altchains-singular pool from which rewards are only distributed to miners (e.g Ethereum blockchain) and Altchains with reward-pool distributed new units for other than mining activities such as content creation (e.g STEEM blockchain).

Smart Tokens-Stacks (B122) are associated with applications running on Altchains (e.g Augur) or with built-in blockchains (e.g Ripple). Smart-Tokens-Stable (B121) interact with the operations of Algorithmic Stablecoins from where their intrinsic value is derived (e.g BitShares token and BitUSD Stablecoins, MKR token and DAI Stablecoins). In more detail, Smart Tokens-Stable (B121) can be used (a) to manage access to execute tasks in a blockchain (e.g the right to mine similar to the concept of the proof-of-stake algorithm) and (b) as incentives in making effective decisions (e.g set interest rates) and acting as price-feeders. Notably, departure from centralized intermediaries presents on-chain problems. Blockchain applications that aspire to interact with the real economy in a decentralized manner necessitate information-feeds, thus coming from off-chain inputs. Therefore, it is inevitably to have some form of centralization even in decentralized cryptocurrencies and this is why Smart Tokens emerged as a necessity. Holders of Smart Tokens are entitled to provide with information the blockchain functionality. In turn, they experience economic benefits in the form of airdropped rewards (new units of the Stablecoin) and price appreciation of their holdings which independently float since higher demand cannot stimulate supply which is fixed.

In general, Tokens under quantity-rules can be used as proof of capital contribution in a project, as proof of ownership of physical assets in the real world, as prepayment for the delivery of a taxable good or service at a premium price (with discount) and more. In particular, Utility Tokens (B11) are issued by for-profit entities aiming to raise funds and in exchange offer rebate (discounts) when services are rendered.

Quota Tokens (B21) refer to a relative new family of cryptocurrencies which aim at stable purchasing power (rather price) and are pegged to quantities of real goods. In other words, the unit of account is the good's standard of measurement (e.g kWh).

Much more ambitious are Algorithmic-Quota (A21) which aspire to both record claims for units of real goods and services. The novel scope is to create platforms wherein users can perform peer-to-peer trading of goods produced in the real economy. Broadly speaking, Utility Tokens and Quota Tokens asset classes stand for the constellation of Distributed Ledgers ecosystems that is directly linked to the real economy for that there is an underlying real asset. Conversely, the intrinsic value of Algorithmic (A1) is their built-in payment system. Since Utility Tokens exhibit strong relations with the real economic activity, it goes without saying that implications such as recognition of revenue and Value Added Tax arise. On other hand, Smart Tokens constitute publicly available digital infrastructures. This means that no billing take places.

Next, our analysis on cryptocurrencies with fixed exchange rate shares common themes with the literature. While Mita et al. (2019) put emphasis on the type of the collateral (crypto, fiat or commodity) in defining Stablecoins, we extend in two ways. First, by separating Algorithmic Stable (A22) from Token Stable (B22) on the basis of the above IOU criteria. Second, and most importantly by distinguishing between (a) under-fully collaterized, (b) fully-collaterized which usually relate to traditional cash (like US dollar), (c) over-collaterized which are collaterized with other on-chain assets (thus, other cryptocurrencies) and (d) non-collaterized at all. It is obvious that "under-fully collaterized" are only available as Token Stablecoins for that reserves are off-chain (traditional currencies). Hence, a legal entity is required to assume obligation. We name these "under-fully" for that the originator is always in doubt about the reliability of his commitment of reserves' full backability. In practice, the issuers usually hire an audit firm to periodically provide assurance over the quality of the statement of financial position. In particular, for Stablecoins we propose the next definition to work with:

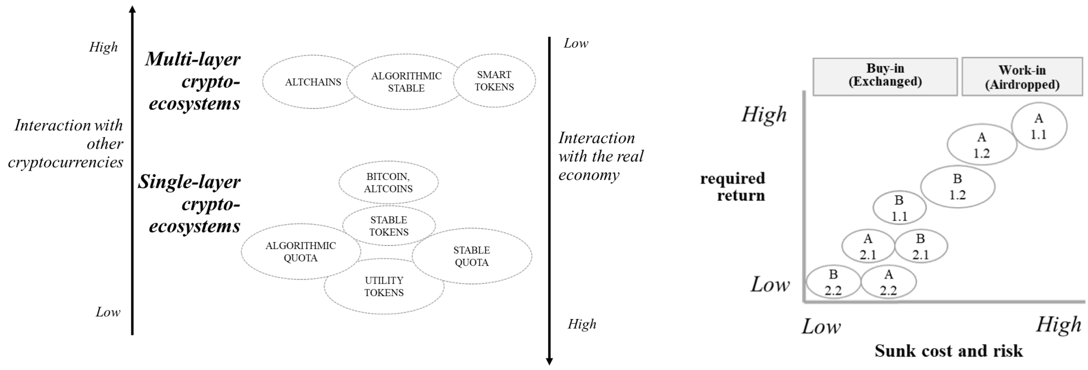
- *Token Stable cryptocurrencies* wherein there is a single cryptocurrency for issuance and governance.

- *Algorithmic Stable cryptocurrencies* operate in an extended ecosystem comprising at least two cryptocurrencies which interplay. Usually, such cases include stable assets pegged to an anchor. Smart Tokens (also called "oracles") with flat supply issued only once require to "work-in" the ecosystem in monitoring the efficiency operation of the Algorithmic Stablecoin by setting interest rates, sell walls, feed the system with off-chain prices.[11]

[11] Here, governance voting-protocols apply. A more complex case is Steem Blockchain Dollar (SBD) which is the Stablecoin of a tripartite ecosystem additionally include an Altchain (Steem) and a non-traded asset called Steem Power.

A more practical distinction between Algorithmic Stable cryptocurrencies and the rest Algorithmic cryptocurrencies (like Bitcoin, Altcoins and Altchains) can be related to how disagreement is resolved. In the secondary category, the solution arrives in the form of forks (creation of new releases). But in the first category, Smart Tokens that govern the stability of Algorithmic Sstable cryptocurrencies have usually a “kill switch”. This is a piece of code that authorizes Smart Token holders to shut down the system (Algorithmic Stable cryptocurrencies) in the adverse event of a severe attack. In the case of collaterized Algorithmic, this means seize and return reserves to their holders via forced liquidation. The next figures depict additional perspectives.

Exhibit 1.6: Interaction and risk-return profiles by asset class




(a) Level of openness

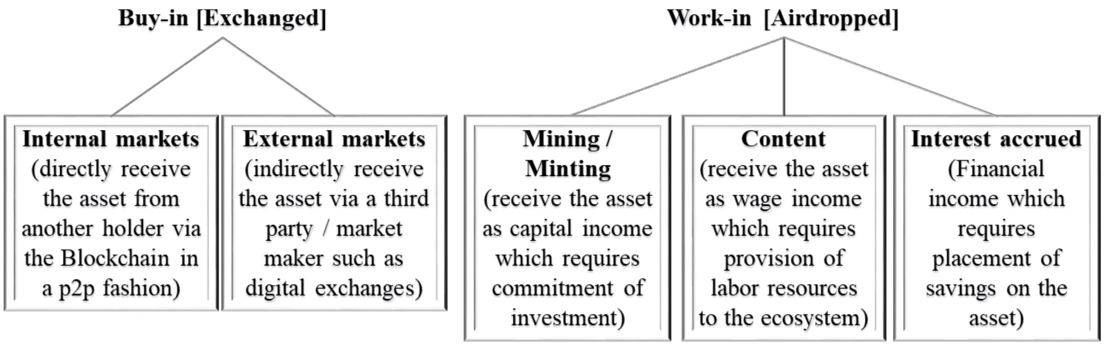
(b) Risk (cost) and return profiles

The figure on the left-hand side shows the the interaction of each cryptocurrency asset class with other ecosystems as commented earlier as well as the interaction with the real economy. Multi-layer crypto-ecosystems and Bitcoin, Altcoins have no interaction with the real economy. Stable Tokens do have but only with traditional cash or commodities. More interestingly, Utility Tokens and Quota-cryptocurrencies endeavor to register rights on real goods in the immutable blockchain.

The figure on the right-hand side illustrates the risk-return profile of these assets on the basis of acquisition. Mining activity involves prior substantial investment, possibly including sunk costs and therefore requires higher return. Cryptocurrencies acquired via exchange either during and Initial Offering (which offer discount as a pre-sale strategy) or afterwards require less return. Even lower returns require assets that were airdropped, thus received without any monetary exchange taking place. Airdropped are referred to as “work-in” involvement in the ecosystem and can relate to reward (a) for mining (as in PoW, PoS), (b) for content (as in PoB) and (c) for interest accrued (as Smart Tokens and

Stablecoins). Conversely, cryptocurrencies exchanged stand for "buy-in" involvement and can be either bought (via exchanges) or received via the built-in blockchain. The schematic illustration is as follows.

Exhibit 1.7: Possible modes for acquiring a cryptocurrency




Noticeably, Bitcoin, Altcoins and Altchains require the highest rate of return for that they precondition investment in capital expenditure and operating expense (electricity). Apparently, another option is to acquire these via exchange (buy-in) with lower require rate of return and risk. Smart tokens and Utility Tokens fall into buy-in options, though note that some may accrue via airdrop after the Initial Offering in the form of interest. Smart Tokens should be perceived as an obligation for that the crowd-sale mandate for enacting an Initial Offering is to provide in the future a blockchain application wherein users can use these "license tokens". The issuer has no liability on the blockchain itself, thereafter, which is distributed in nature, thus maintained by the users.

On the other hand, Stable cryptocurrencies do not bear any nominal rate of return. Decentralized (Algorithmic) are conceived more risky than centralized (Token) for that the latter are backed by issuer's (a company) liability. Stablecoins emerged as a market need. When cryptocurrencies are exchanged for traditional currencies via digital exchanges transaction costs in the form of handling fees occur. So when active trading takes place the cost for the investor raises as well. Therefore, Stable cryptocurrencies particularly the ones that are pegged to a traditional currency ease exchange and boost volume. As a matter of fact, since the development of USDTether Stable cryptocurrency it has been observed that the trading pair Bitcoin / US dollar has been gradually replaced by the Bitcoin / USDTether market. All said, high concentration is observed in the ecosystem for that the 10th percentile of all cryptocurrencies mostly fall into the 90th percentile of the entire market capitalization and almost for the 99th percentile of the entire trading volume.

## 1.5 A political economy discussion

The financial technology of Distributed Ledgers has introduced new perspectives to money, finance and banking. This section broadly discusses four political economy issues.

### 1.5.1 Initial offerings & policy implications

It is safe to say that cryptocurrencies have low interaction, so far, with the enterprise world. This means, unfortunately, not only that users are natural persons, but that established firms rarely accept payments in cryptocurrencies or are willing to perform an Initial Offering. An important impediment for firms entering into crypto-transactions is the absence of commonly accepted regulatory frameworks. There are countries which regard some cryptocurrencies as securities. This is not a simple case where all Initial Offerings are similar and similarly regulated. It it should be emphasized that all Initial Offerings are pre-payments. Either for developing a digital infrastructure (a software) publicly available as in the case of Algorithmic coins. For example, the Ethereum Foundation, a non-for-profit entity which collected the funds in its Initial Offering, does not apply any usage-based billing or similar revenue models for that following its launch the blockchain is sustained by the peers (users) not the organization. Or for developing a private project by a for-profit firm.

On the basis of the taxonomy earlier contributed, we expand to show how Initial Offerings by cryptocurrencies under quantity-rules should be distinguished. We further suggest the next financial reporting treatment:

- **Initial (Algorithmic) Coin Offerings (ICOs)** are closer to a hybrid form of "unconventional equity". This entails that these funds should be taxed for capital contributions in accordance with national laws, if applicable but the funds do not claim any voting rights or shares of the issuer. While this account could resemble to an equity reserve account, these funds should be restricted from distribution in the form of dividends.

- **Initial Utility Token Offerings (IUTOs)** are closer to a hybrid form of debt for that are pre-payments for taxable goods. This means that a short-term liability account should be recognized on the originator's balance sheet. At issuance any relevant tax duties and stamps should be paid for that this is a lending facility. At exercise, thus when these are redeemed to the issuer for paying outstanding invoices, the corresponding direct taxes (VAT) with regards to the underlying good should be settled. It follows that the Token value incorporates both the net value and any direct (value adding tax) and indirect taxes (income). A last comment. As Tokens return to the originator for payments, the initial debt issuance should be correspondingly amortized. This includes cases of voluntarily destroying supply (e.g BinanceCoin). Originators should always recognize a liability account so as to indicate the level of money supply and the quality of backability of these Tokens on the balance sheet.

- **Initial Smart Token Offerings (ISTOs)** are a particular case. The trouble arises because there is no usage-based billing by the originator since there is no underlying real good delivered by a legal entity. These assets can be treated either as "unconventional equity" or even regarded as taxable donations. It is much preferable to speak of the former as the advised treatment than the latter. For the only reason why these are distinct from Algorithmic coins is because the latter are scarce; and they are kept scarce because of the algorithm. But Smart Tokens are not scarce at least in the economic sense for that are issued only once just like equity shares. This is critical because they incorporate higher risk (if someone controls the supply) compared to Algorithmic coins which are programmed to continue grow just like commodities. There are all sorts of reasons why these cryptocurrencies should be scrutinized as concealed securities (promising free capital to uninformed investors) and not the above two categories.

It is evident, then, that international accounting standards will soon be challenged to cover this discrepancy. In the case of Bitcoin, it has been excepted from indirect taxes.[12] This should apply to all cryptocurrencies for that all stand for cash. Lastly, there is another important policy issue. The income from "working-in" the ecosystem (mining etc.) and capital gains earned from the sale of cryptocurrencies. Are these taxable? In the literature there is no clear consensus and further studies are recommended aligned with the above policy implications.

### 1.5.2 The inalienable civil right to anonymous cash

This discussion can include a very timing case, that is the argument of phasing out cash (coins and banknotes). This is not new. In the early 1990s, the Mondex smart card electronic cash system using stored-value (anonymous) cards was launched by the National

[12]The Court of Justice of the European Union has ruled that the services of a Bitcoin exchange in exchanging Bitcoin for a traditional currency is exempt from VAT on the basis of the "currency" exemption. See, Judgement in Case C-264/14. Skatteverket v David HedqvistâĂİ. Press Release No 128/15, Luxembourg, 22 October 2015.

Westminster Bank.[13]. The alleged claim was to replace cash, but this project never went nationwide. In nowadays, cash which consists of coins and banknotes allowing agents to transact in a peer-to-peer anonymous fashion without any watchdog intermediary stands for no more than 5 per cent of base money. Yet, what would be useful is to contribute with how cryptocurrencies pertain to the debate of phasing out cash.

According to Rogoff (2014) the counterarguments include (i) increased risk at central banking independence due to loss of seigniorage, (ii) disruption of common social conventions for using money (possible decline in demand for debt), (iii) the contagion effects as if a country reduces the use of paper-money there is a risk that another country's means of payment might be used domestically and therefore this process can only be taken up institutionally among countries and finally, of course (iv) the issue of civil liberties that metallic and paper (anonymous) cash should adhere to.

In a world without cryptocurrencies, the discussion about phasing out paper-currency would imply the empowerment of the quasi-free banking system as all transactions would be centrally (and not anonymously) recorded. Clearly, this point is political. In that sense, phasing-out does not entail replacement of this operation. Let us take it up from the last point made by Rogoff (2014) and the issue of civil liberty. It is true that one of the major qualities of paper-currency is anonymity. If high-powered money (paper-currency) is phased out all transactions will be conducted via the system of accounts maintained by the commercial banking sector, thus anonymity of paper-currency is lost. But, maybe the cryptographic algorithm of cryptocurrencies which by construction secures at least pseudonymous identities could resolve this issue. The recent initiation of a series of research programs and studies (Barrdear & Kumhof, 2016) on Central Bank Digital Currencies (CDBC) possibly signals the development of alternative central banking instruments of digital nature.

### 1.5.3 Institutional perspectives of alternative money

Such complex monetary systems might be more efficient but if they are effective is highly debatable. An alternative kind of currency for cash transactions may resolve hoarding of the currency which is hurting commerce. This is the case of Bitcoin. Another political argument here is who has access to digitization. Practical obstacles do exist such as the infrastructure required (internet) which is absence in less-developed countries. Also the technological knowledge required to use a cell phone or a Personal Computer (PC) which is present due to demographic reasons (elders). Paper-money has a physical substance.

[13]Source: British Museum and the United Kingdom cards association (2017)

Mobile-phone has a physical substance and, therefore, currency could be replaced, yet this would require that every mobile-phone has continuous access to the internet. Cash provided by formal institutions like central banks do not require such infrastructure and it is difficult to think how cryptocurrencies can compete this advantage.

Furthermore, the sustainability of cryptocurrencies as informal (money-issuance) institutions is considerably questioned. But, do we have a working definition of institutions and informal ones in particular in order to support this claim? According to Coase (1960) an institution, and subtly centralization emerges on account of transaction costs. But, centralization comes with order (laws by decree), and therefore uncertainty and concern for the concentration of institutional power is raised. In the same spirit, cryptocurrencies meet this condition as they significantly reduce current banking costs both in nominal and real terms. Distributed Ledgers applications allow less costly (cheaper) and less timely (faster) transactions. By way of example some cryptocurrencies may settle transactions within 1 minute where traditional banks require at least 1-2 working days for settling remittances. In examining the institutional case of Bitcoin, Smit et al. (2016) also endorse that reduction in transaction cost stands for the sole sufficient and necessary condition in characterizing an asset as money.

Alternatively, there is another conceptual way to attest this. In an interesting approach, Brunner & Meltzer (1971) as cited by Vaubel (1986) argue that money itself is a substitute for information because inherently it reduces transaction cost. To extend this, if we accept cryptocurrency nature as money then by inductive reasoning we can ascertain its informal institutional nature. In the literature, S. Davidson et al. (2016) collect concepts from Hayek (on distributed knowledge), Elinor Ostrom (on commons governance), Oliver Williamson (on incomplete contracts), and James Buchanan (on constitutions and collective action) in supporting that blochchains represent not a new type of technology, rather a new type of economy, thus a "catallaxy", a conceptual epistemology conveyed by Hayek (Vaughn, 1999). However, the long-term sustainability of such non-centralized systems are still not entire persuasive, especially with respect to the underlying political environment. For Markey-Towler (2018), when talking about blockchain system in particular, thus for non-monetary applications, these are, in principle at least, anarchic.

### 1.5.4 Anarchy, and the utopia of non-centralized currency

The social dimension of Algorithmic cryptocurrencies and the potential link to anarchy has already concerned scholars (Dodd, 2018; Markey-Towler, 2018). When thinking about anarchist environments, an odd, yet practical question arises, that is "how does exchange take place"? To pose this puzzle more practically what kind of monetary systems should we expect to emerge if we were to assume that anarchist societies are not an utopia. By virtue, anarchist societies reject any kind of centralized organization, intervention and government (Nozick, 1974).

Historically, money has been provided by sovereign authorities i.e. governments and regulated banks. So, how does exchange occur in an anarchist society? Should we expect a pure barter economy, which inevitably drives us to conclude that due to high transaction costs, immense inefficiencies would emerge resulting to impossibilities in exchanging the wealth produced. In the main, the backbone of this type of thinking is dealing with the issue of non-governmental currency. But what if cryptocurrencies were used as media of exchange in such environments since they allow for (a) non-barter, (b) geographically distant and (c) non-authoritarian regulated transactions? The implication is that Algorithmic cryptocurrencies stand for the first practical solution to the political economy problem of monetary exchange found in anarchist societies.

## 1.6 Concluding remarks

Economic history is often dismissed as of little utility but its use as evidence is always helpful. It is not the first time that an unusual and uncommon innovation challenges literature and the economy as a whole. In around 1250, "Societe des Moulins du Bazacle", a French company based in Toulouse issues to the public 96 shares and introduces for the concept of "joint-company ownership". In 1494, Luca Pacioli, an Italian Mathematician, collaborator of Leonardo Da Vinci and Venice-based merchant writes a work with the long title "Summa de arithmetica, geometria. Proportioni et proportionalita" where he introduces the fundamental concepts of "double-entry bookkeeping". These are arguably two of the most important inventions in the entire enterprise history. It is an open question whether Distributed Ledgers would become the next one.

# Chapter 2

# A survey of the Distributed Ledgers literature. A ten-year commemoration

We accumulate the scattered pieces of Distributed Ledgers' history and research in commemoration of the first decade of the literature produced from the advent of Bitcoin. On the grounds of this, this paper provides historical perspectives and inquires what economic elements embedded in cryptocurrencies and blockchains motivated the establishment of this growing area of research. Then, the paper reviews and categorizes the most significant extant literature. The emphasis is on research methods employed and results delivered relating to the conceptual, theoretical and empirical contributions through the ages that have influenced the chain of evolution of this still uncharted literature.

## 2.1 Introduction

The notion of Distributed Ledgers refers to the peer-to-peer (p2p) technology that underpins the continuous diffusion of varieties of blockchain and cryptocurrencies first introduced by the work of Nakamoto (2008). Blockchain is a shared database wherein transactions are verified among peers (computers called full-nodes that are connected to the network and run the software), thus without the need for a third party, and recorded in chronological order in a transparent and irreversible manner that is highly improbable to tamper with. The unit of account and the media of exchange (for paying fees where is applicable) in such decentralized payment systems which rely heavily on cryptography and in particular hash functions[1] to achieve security is colloquially referred to as cryptocurrency. This digital asset is divided in decimals just like traditional currencies and is exchanged via addresses and passwords (similar to the concept of electronic mails) which are documented in the form of alphanumeric characters (collection of strings and numbers).

The monetary nature of this asset is cash for that the transactions and holdings are anonymous (or at least pseudonymous) just like cash at hand, thus similar to coins and banknotes. Hence, unlike Commercial Banks' checking accounts which handle personally identifiable information. The financial nature of this asset can vary. It can bear resemblance (a) to commodities, thus the case of Bitcoin and Altcoins, Altchains alike wherein the supply schedule adheres to a pre-determined increasing path at a decreasing rate making them scarce via a competitive process among full-nodes that hold a copy of the complete history of the blockchain database which they continuously update after the validation of new transactions based on a consensus algorithm whereby the winner(s) receive as a reward the newly "mined" or "minted" units as called for. Also, (b) to financial debt instruments (IOU) issued once, thus their supply is fixed (case of Utilitycoins). Even, (c) to electronic deposits where supply expands but contracts as well (case of Stablecoins).

Over the past ten years, therefore, many other applications of blockchain databases and cryptocurrency assets have been developed marking a flourishing research field not limited to Bitcoin. There have been observed more that 5.000 cryptocurrencies offerings so far, and these can be broadly classified as (i) Altcoins, thus clones of Bitcoin, (ii) Altchains which offer alternative blockchain platforms (the most popular case being Ethereum whereby new cryptocurrencies can be easily created and circulate on the built-in Ethereum blockchain, thus without the need for developing a separate blockchain), (iii) Utilitycoins which represent IOU digital assets (acceptance for future payments) initially used for financing start-up projects and (iv) Stablecoins wherein their exchange rate is pegged to an anchor, usually the US dollar (USD) at parity.

Today (as per March 2020), a deep secondary market has been established with more than 20ths. available markets (trading pairs offered by numerous private digital exchanges). Market capitalization, a term used in equity securities but also used in cryptocurrencies to denote the product of current price (exchange rate) times units of

[1] Hash functions can satisfy two important properties. They can be used to convert data of arbitrary size to fixed-size values very fast via a deterministic procedure (thus for a given input the output must be always the same hash value) but the computation going backwards is impossible. The latter means that in these one-way functions, knowing the hash value you cannot simply reverse the process to calculate the initial data.

circulating supply amounts to approximately USD 200 bil. and daily volume amounts to approximately USD 150 bil. Bitcoin's current market share is less than 65%. On the other hand, blockchain prototypes can be distinguished between (a) without-permission, thus fully open and untrustworthy payment networks where anyone can view and validate and (b) with-permission where access rights are granted by invitation while various consensus algorithms continue to emerge.

A synthesis, however, (a) of the historical perspectives prior to Bitcoin, (b) the source for research's motivation spurred by the above mentioned financial technology developments and (c) existing research trends that can collectively portray the evolution of the understanding of both blockchain and cryptocurrencies is still missing. The remaining of this paper is organized as follows. Section 2 collects the historical events in related disciplines that led to the inception of Bitcoin and eventually its launch in early 2009. Section 3 sets the literature milieu and points out the four elements that drive research motivation. These correspond to four innovative features of unprecedented economic nature embedded in cryptocurrencies and blockchains. Section 4 reviews and classifies the research methods employed and the central contributions delivered through the ages (2009-2019). The last section concludes and extends on future research.

## 2.2 Setting the literature scene

Let's first equip this literature review with the appropriate conceptual framework to include a brief explanation of technical terms. Electronic currencies consist of traditional banking systems and virtual/digital currencies. The former refers to Commercial Banking electronic deposits denominated and convertible sovereign currencies (coins and banknotes) which in the literature are referred to as system of accounts (E. F. Fama, 1980). On account of the common unit of account, research on Central Bank's currency (coins and banknotes) and commercial banks' system of accounts (deposits) coincide. Currencies of digital nature did not arrive with cryptocurrencies. Earlier attempts to issue virtual currencies made by private firms and on-line games in the early 90s can be viewed as the ancestor of cryptocurrencies. But, the pursuit for broader acceptance of these means of payment and adoption in the real economy ended to failure. There was an element missing. What could guarantee that the issuer does not "print money" with reckless abandon and that transactions are truthfully recorded? This gave the idea of a currency with limited (scarce) supply, called cryptocurrency and a shared public database, called blockchain whose cryptographic architecture can ensure transparency and safety. Bitcoin is the first prototype which combines these two features. In the literature, these peer-to-peer environments are referred to as Distributed Ledgers for that distributed networking and ledgers bookkeeping collaborate. Below, we elaborate on these research borders by offering an introductory survey of the literature on (a) virtual currencies and economies, thus other than electronic deposits issued by commercial banking for that this falls under the more general literature of traditional currencies and on (b) cryptocurrencies in Distributed Ledgers.

### 2.2.1 Virtual economies literature

In 1996, a virtual currency convertible to gold called [E-gold] was introduced by a US private firm, and in its aftermath research interest in virtual currencies begins. Birch & McEvoy (1997) attempt to identify taxonomy standards to distinguish between physical and digital items. Notwithstanding, research on virtual economies within the economics remit, unmistakably commences a few years later with two awe-inspiring works prepared by the same person namely "On Virtual Economies" (Castronova, 2002) and "The Theory of Avatar" (Castronova, 2003) who pioneered a new kind of economic research. In short, Castronova develops a demand theory applied to the case of a virtual MMORPG game[2] to determine that economic theory (branded by himself as *earth economics*) as known is not applicable in virtual economies where *avatar economics* (another Castronova brand) run things. Differences primarily concern price control, disutility (in avatar economy leisure is bad), growth and population (choice of economic agent).

In close relation, H. Yamaguchi (2004), publishes a paper with the title "An Analysis of Virtual Currencies in Online Games" whereby further examines virtual currencies used by gaming players. He classifies such currencies as Local Exchange Trading Systems (LETS) because they are used in limited communities, not under control of money supply by the central banks, and are not subject to interest rates. He adds that the virtual currencies have exchange rates with real currencies, and thus have become meaningful for the economy. Lehdonvirta (2005) follows these developments and shares the dire need for studying the microeconomic and macroeconomic substances of these virtual economies. This was enough to motivate Ernstberger (2009) who first studied how to model monetary policies within a virtual currency environment.[3] Since then, this area of research combining technology and the digital economy started to shrink and, in effect,

[2]MMORPG stands for massively multi-player online role playing game). The game examined is called EverQuest, released in 1999. Later on, in 2004, World of Warcraft released, another MMORPG introduced its own internal currency as means of payment.

[3]He uses as case study [Linden Dollars], an internal means of payment for the on-line game called "Second Life" launched in 2003.

replaced by research on Distributed Ledgers.

### 2.2.2 Distributed Ledgers-economies literature

In 2009, Bitcoin becomes the first ever cryptocurrency and research commences a few years later probably with Grinberg (2011) in legal studies. The study of Bitcoin, Blockchain, cryptocurrencies and Distributed Ledgers in general draws on knowledge from different scientific disciplines. To our best of knowledge, academic research on cryptocurrencies is also available in the literature of Information Technology, Politics[4] Sociology[5] and Law[6]. From this point and thereafter, this survey of the literature only discusses works relevant to Distributed Ledgers (DL in short) from the economic literature viewpoint.

A critical comment at this point. Note that it is still open to debate whether Central Bank Digital Currencies (CBDC) controlled by a sovereign authority which also controls sovereign / national currencies, should be related to cryptocurrencies and, in turn to the Distributed Ledgers literature. In this work, we argue that this should be the case on the basis of two criteria. Hence, as far the (a) blockchain which records transactions is public, thus can be viewed and accessed by the general public and (b) the holdings are at least pseudonymous, thus similar to cash at hand as in the case of Bitcoin.

### 2.2.3 Research motivation & the way forward

We have been dealing so far with a constellation of payment systems and assets spurred by the Distributed Ledgers ecosystems. We must, however, explicitly identify in a more practical sense the research areas challenged and why. There are four innovative spin-off features from these ecosystem that are of great research interest for that they deliver new frameworks of:

1. auctioneer (in clearing)
2. organization (in governance)

[4]From the politics point of view see article: Bitcoin: The Cryptopolitics of Cryptocurrencies by Harvard University Press, 2014

[5]From the sociology point of view, see Dodd (2017)

[6]From the law point of view, Marian (2013) first relates the absence of regulatory laws and by-laws with taxation and trading of illicit commodities via digital/virtual networks. Micheler (2015) supports that *distributed consensus ledgers* could alleviate custody risks associated with holding and transferring securities to which owners are currently exposed to while Nabilou & Prüm (2019) is concerned with central banking regulation.

3. money (in exchange)

4. capital (in financing)

These four features are the next. Note that the first two features are associated with the blockchain blueprint and the other two to the cryptocurrency blueprint. In particular,

1. Full-nodes' mining/minting

2. Hard and soft Forks[7]

3. Algorithmic cryptocurrencies and Tokens

4. Initial Coin and Token Offerings (ICO, ITO)

It is due to the unprecedented economic nature of the above four features that motivated the literature to engage in research studies. In sum, market design literature is interested in Blockchain operations as a payment system and in specific in the first two features. Applications on macro-banking level literature and asset pricing literature are interested in the asset, thus in cryptocurrency operations and therefore in the other two features. The schematic illustration is offered below.

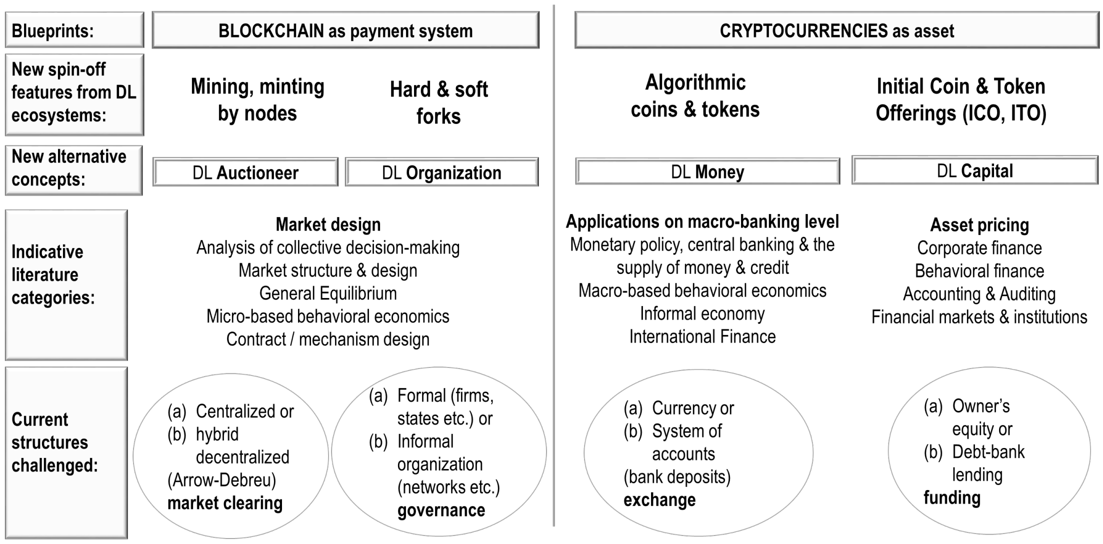
The next working is to further delve into the context of these research challenges and, in turn support the argument that Distributed Ledgers have introduced new alternatives to well-established puzzles and research areas. If true, then the impact of blockchain and cryptocurrencies on the economic literature should not be considered immaterial.

### Blockchain as DL auctioneer

*Background*: Market clearing has been always assumed to take two forms namely via (a) an assigned centralized party where issues of information asymmetry inevitably arise such as principal-agent problem or (b) an implicitly assumed auctioneer in a "hybrid-decentralized" environment. With relation to the latter, DL serve as payment systems that seem to enable market clearing and prevent double-spending in a unlike manner in comparison with the *Walrasian Tâtonnement* process implicitly assumed in standard decentralized General Equilibrium Arrow-Debreu models. "Double-spending problem" is

[7] Forks are divided into two categories i.e. permanent and temporary. The latter are temporary disagreements between peers as arrive to consensus in the network for the true state of the Blockchain. The former are distinguished between hard and soft Forks. Soft Forks refer to disagreements in functionality and need not to upgrade. Hard Forks refer to planned petition whereby peers decide which version to follow after the spin-off of a new cryptocurrency.

Exhibit 2.1: Panorama of the Distributed Ledgers literature




the act of spending the same asset with the property of uniqueness (such as money) more than once at the same time. Mainstream economic theory subtly postulates that market clearing is conducted via that fictional figure (the *Walrasian auctioneer*), thus implicitly is centralized, yet explicitly not since money does not exist in such environments ( *"money is merely a veil"*).

*Challenges*: But, where do Blockchain fit in this theoretical abstraction? Blockchain is not a centralized system rather a flat system where only one type of agent exists i.e. "nodes". Therefore, the problem of principal-agent disappear and must be replaced by a different one. Hence, the information asymmetry puzzle is challenged to study how specific operations such as agreement, settlement, clearing, self-enforcement of such peer-to-peer economics networks related to the available consensus algorithms come forth. The main matter is how non-hierarchical processes such as mining/minting whereby verification of transactions takes places by the peers of the system among who could be malevolent participants will survive and not end up to closure or fraud.

*Applications*: Furthermore, in which market places could the economy witness implementation of this new kind of auctioneer for market clearing? Some examples may include stock markets, intra-banking communication, exchange of information between branches of an industrial entity, State's tax systems such as value added tax, customs-duties, public notary services and much more.

### Blockchain as DL organization

*Background*: Organizations and collective decision-making are well-examined in the economic literature. Organizations come in two flavors namely (a) formal like firms, states and international institutions and (b) informal like networks or community practices for governing the commons. Such type of organizations yield significant inefficiencies and the main research puzzle in this field focus on externalities in corporate governance and social choice. In this frame, members of the community must make individual decisions and bear the ramifications of collective decisions.

*Challenges*: But, in DL organizations, externalities can be limited for that decisions can be made on individual basis without affecting others on account of the technological idea of Forks.[8] Hence, the main research question around blockchain is whether cane the first working paradigm of pure decentralized organization. If this is true leads to deduce that their organizational nature is unparalleled and their impact on the economy is of undetermined significance.

*Applications*: Furthermore, possible applications of DL organization may be seen in electoral systems and political/economic debates. For example this new kind of governance may offer a way-out to the recent debate about the public will expressed in referendums. In DL organizations, disagreement is resolved by the formation of sub-organizations where peers that share the same vote collude and depart from the community without imposing externalities to the rest of the society.

### Cryptocurrencies as DL money

*Background*: In monetary economics, pure decentralized environments require the existence of "geographically distributed trades" among peers. A couple of years prior to Bitcoin inception, Blanchard (2000) enlightens the circumstances under which money enters into pure decentralized monetary scheme i.e. in the absence of a centralized auctioneer. He explains that if this is the case (no auctioneer) then it results in causing the problem of "double coincidence of wants" and barter is a solution but it impedes transactions. As a result, we deduce that money has to emerge to play the role of medium of exchange in an akin manner with p2p connectivity in information technology which accounts for resolving the problem of "double spending" as pointed up. Buchholz, Delaney, Warren, & Parker (2012) give the impression that align with our argument in

[8]The first (hard) Fork happened in August 1, 2017 with Bitcoin Cash. Hard forks are like new updates of the cryptocurrency software and allow participants to freely decide whether stay with the old version or follow a new one. Note that soft forks suggest minor changes to network and do not result to creating new versions.

their own conceptual approach on this matter.

*Challenges*: But, then it arrives as a natural consequence the idea that cryptocurrencies may fit in this theoretical abstraction where geographical distant trades are available like in exchange via the banking system of accounts (deposits) and anonymity is prevailed just like in exchange via currency (coins and notes). For it is, so to speak a new kind of monetary (non-barter) exchange, revisiting the traditional money and banking literature for the exchange of wealth (E. F. Fama, 1980) could be required.

*Applications*: Furthermore, what intrigues research on cryptocurrencies is whether there is a way to design efficient cryptocurrency monetary systems to work in tandem with sovereign currency on the basis of tamper-proof, rule-based production, publicly auditable governance, merit-based distribution, fast and low-cost transaction fees. Most certainly it would irrevocably alter the elements of Central Banking and international trade.

### Cryptocurrencies as DL capital

*Background*: In theory and practice, capital additions (new funds) arrive in two forms i.e. (a) equity, thus contributions by the owner acting as residual claimants and (b) debt, primarily in the form of bank-lending. It is true that cryptocurrencies, in particular the ones that involve the raise of traditional currency in exchange for cryptocurrencies (usually called Tokens) are a hybrid form of capital to combine features from equity (when rights to the network are assigned) and debt as prepayment for goods (either in digital form such as payment fee or real goods) rather a typical credit-line to be paid back in traditional currency.

*Challenges*: But, as this unconventional form of raising capital by firms through a process colloquially referred to as Initial (Coin or Token) Offerings via the Distributed Ledgers technology[9] continue to gain substantial traction, then optimal capital structure puzzle could have another element. As capital structure is not irrelevant in the real world for that the neoclassical assumption do not hold, the traditional finance literature (Modigliani & Miller, 1958) may be revisited in a critical manner by this advent of centralized Token cryptocurrencies.

Furthermore, what also fascinates research with the idea of cryptocurrencies is that of reducing transaction costs. And, for finance there is something more. Cryptocurrencies as an alternative to holding bank deposits might make the liability of holding assets

[9]Initial Offering is a process whereby funds denominated in cryptocurrencies (usually Bitcoin or Ethereum) are collected to finance a project initiated by a private organization. The first ICO happened in 2013 (Mastercoin, currently named OMNI).

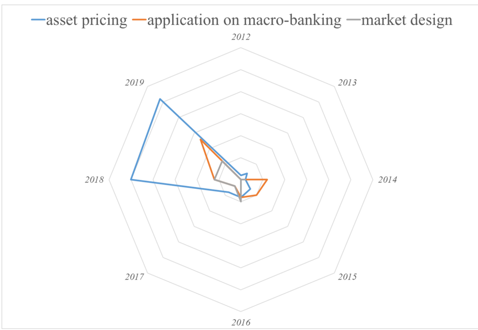
redundant. This benefit is similar for Information Technology and traditional centralized digital (server-based) services which are vulnerable to security problems (hacks). In banking, holding assets (including customers' database) entails cost, which in turn increase prices.

*Applications*: Furthermore, applications in this concept are numerous and the impact would be on commercial banking activities. Offering of cryptocurrencies might be at last a reliable competitor to the long-lasting non-competitive bank lending. Interesting applications include non-for-profit activities for that the immutable blockchain digital footprint allow could replace unclear in purpose and use donations in traditional currencies with in-kind-donations denominated in cryptocurrencies which are exercised (redeemed) for the acquisition of goods.

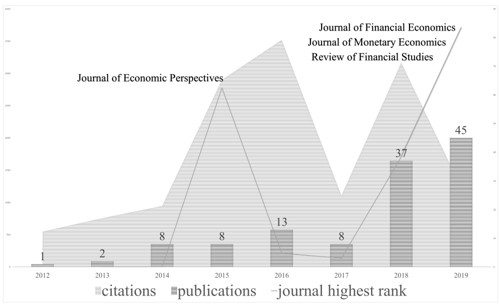
## 2.3 Current research & trends

This section casts the position and magnitude of research on Distributed Ledgers across all branches of the economic literature. In a broader and more pragmatic context, the next figure on the left showcases the evolution of publications by each literature branch while the figure on the right exhibits the evolution of publications, citations and journal ranking throughout this ten year commemoration.[10]

Exhibit 2.2: Bibliometric analysis of the literature through ages




(a) By literature branch




(b) Publications, citations, journals

It is self-evident from the figure on the left that an explosive reaction to cryptocurrency market capitalization peak in late 2017 (surpassed USD 700 bil) occurs in the years

[10]We recruited the sample of 122 publications over the last ten years. Source for citations: *Google Scholars* as per November 30, 2019. Source for journals: visit *rankingideas.repec.org* as per November 30, 2019. Note that journal ranking line indicates the publication hosted by the journal with the highest rank in each year.

2018-2019 driven by the financial economics branch. As far as journals, on the basis of prominence (highest rank), are concerned, a study on Bitcoin was first published in the *Journal of Economic Perspectives* (ranked 8th) in 2015, then in the *Review of Financial Studies* (ranked 12th) and in the *Journal of Monetary Economics* (ranked 13th) in 2018 (also in 2019) and in the *Journal of Financial Economics* (ranked 6th) in 2019.

It is interesting to note that the research topic of Distributed Ledgers is mentioned, thus not independently studied and published, in two works in the *Journal of Economic Literature* (ranked 2nd) in the year 2016 (entitled *The Economics of Privacy*) and in the year 2019 (entitled *Digital Economics*). In these works the word "Bitcoin" and "Blockchain" appears one and four times respectively. In the former, Acquisti et al. (2016) signals the consequential, not to be taken for granted, characteristic of privacy in cryptocurrencies. In the latter, Goldfarb & Tucker (2019) praise this "promising technology" and address what this literature review also intends to that is, the prospect

> ...we might see *a diverse literature emerge over the next few years* on the consequences of low-cost verification-and the associated *changing role for intermediaries...* [emphasis mine]

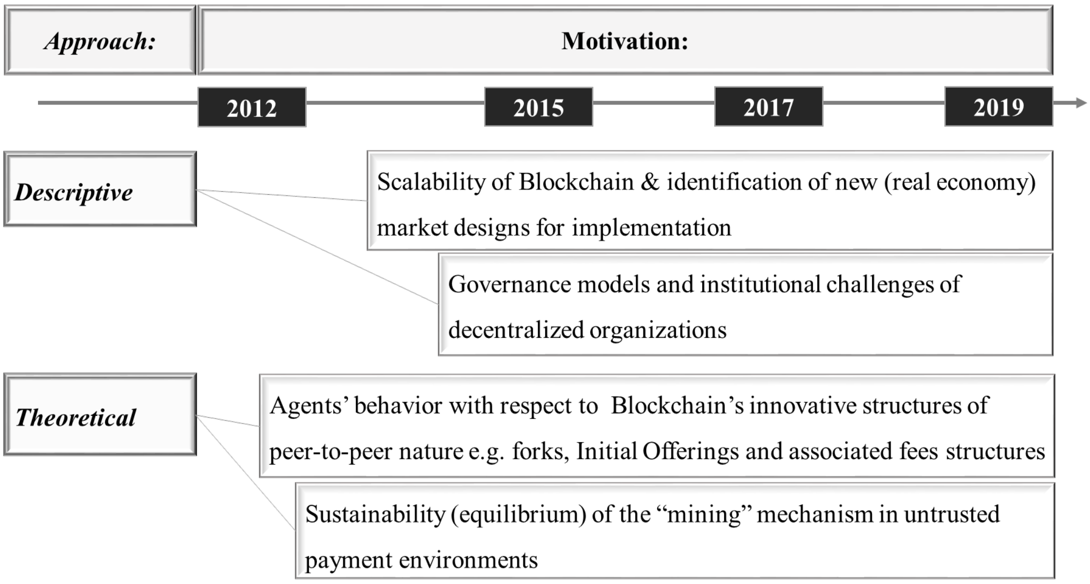
The implications of the growth of this literature has hitherto been emphasized. Some scholars have prescribed the formulation of new categorical fields within economic literature remit labeled as *cryptoeconomics* (Zamfir, 2015; Hsieh et al., 2018) and *cryptofinance* (Harvey, 2016).[11] It is, therefore, agreeable to, our own thoughts that two general categories of the JEL classification could incorporate these latest developments. In particular, the category named "P: Economic Systems" could include a new sub-category entitled "peer-to-peer systems" and the category named "O: Innovation, Research and Development, Technological Change, Intellectual Property Rights" could include a new sub-category entitled "Distributed Ledgers Innovation".

### 2.3.1 Survey of the literature on Blockchain market design

The next figure outlines the research methodology followed in the field of market design with respect to blockchain structures.

[11] The term "cryptoeconomics" seems to first appear in computer science literature in the mid-90s in relation to cryptography and e-commerce (May, 1995; Joseph Jr et al., 2005). The latter is a work entitled "Trust in electronic markets: The convergence of cryptographers and economists", originally published in 1996 (Reagle Jr et al., 1996).

Exhibit 2.3: Evolution of the related market design literature




### Descriptive: governance and applications

As a first step, Gervais et al. (2014) set the question whether Bitcoin is indeed "fully" decentralized and openly raise concerns about the sustainability of blockchain's core operations such as decision-making, mining, and incident resolution processes. The same issues equally excite Böhme et al. (2015). A few years later, Catalini & Gans (2016) assert that blockchain operations are not void from cost and pinpoint the two focal costs associated with the Distributed Ledgers systems namely the cost of verification and the cost of networking. For Abadi & Brunnermeier (2018) blockchain faces an impossible trinity, thus the constraint of simultaneously achieve (i) openness, (ii) correctness (fairness) and (iii) cost-efficiency. At the same time, S. Davidson et al. (2016) introduces Distributed Ledgers to the institutional economics literature. In this work, the authors examine blockchain as a new economy rather as a new technological arrival in the economy and very interestingly relate blockchain's structure to concepts from Ronald Coase's about efficient institutions, Elinor Ostrom about commons governance, Oliver Williamson about incomplete contracts and James Buchanan about constitutions and collective action.

A comprehensive research framework which collects the current applications of the blockchain technology in the real economy can be found in Risius & Spohrer (2017). Many proposals have been drafted and some have lived up to to receive funding via token funding. Applications include adoption of blockchain verification systems in supply chain management, public notary services, peer-to-peer trading in the renewable energy sector between prosumers, tax registration and much more. In Yermack (2017), we find similar considerations about the replacement of traditional centrallly organized structures. Not far away from this point, Jacobs (2018) broadens the discussion to propose the potential of building transnational global blockchain-based governance structures in the economy in his own stance for this topic.

Going to the offsrpings of the blockchain innovation, thus after Bitcoin, Hsieh et al. (2018) sheds light, from the organization design perspective, on the functionalities of the so-called Decentralized Autonomous Organizations (DAO) introduced by Altchains, thus alternative to Bitcoin Blockchain which are platforms for the execution of ad-hoc smart contracts by the user (e.g. Ethereum). In Hacker (2019), by contrast, financial innovation brought after Bitcoin such as Token sales (Initial Coin Offerings and alike) is seen with skepticism for that are prone to fraudulent activities, as has already happened due to lack of robust governance frameworks. This discussion on the features of governance in blockchain ended up as mostly anticipated to study and relate it to anarchy (Markey-Towler, 2018).

### Theoretical: sustainability & equilibria

This strand explores the behavior of agents in such peer to peer networks wherein no central planner is implied rather operate on the basis of *ex-ante* (pre-defined) production-distribution incentive-driven behavioral mechanisms. Blockchain calls for the careful examination of their limitations and potential in terms of sustainability and stability. The fundamental puzzle from the microeconomics perspective is to find the sufficient and necessary conditions for these distributed economies to survive and not die out in the foreseeable future. It is well-known that the *going concern* assumption is binding in both sovereign organizations for that the law decree lays down their establishment (authority) and in business organizations in the pursuit of *profit*. But, how are Distributed Ledgers designed to meet this sustainability goal?

Interesting enough, research seems to, partly apply mechanism design concepts from the microeconomics literature. Kroll et al. (2013) was one of the first to examine the existence of Nash equilibrium in the mining mechanism (the process whereby transactions are validated by the peers of the system) to argue that Bitcoin will call for governance structures contrary to today's ungovernable view. In the same spirit, Caginalp (2018) offer a broader model with three key parties namely agents with savings at risk, a dictatorial government and speculators examining game theory strategies within different equilibrium possibilities.

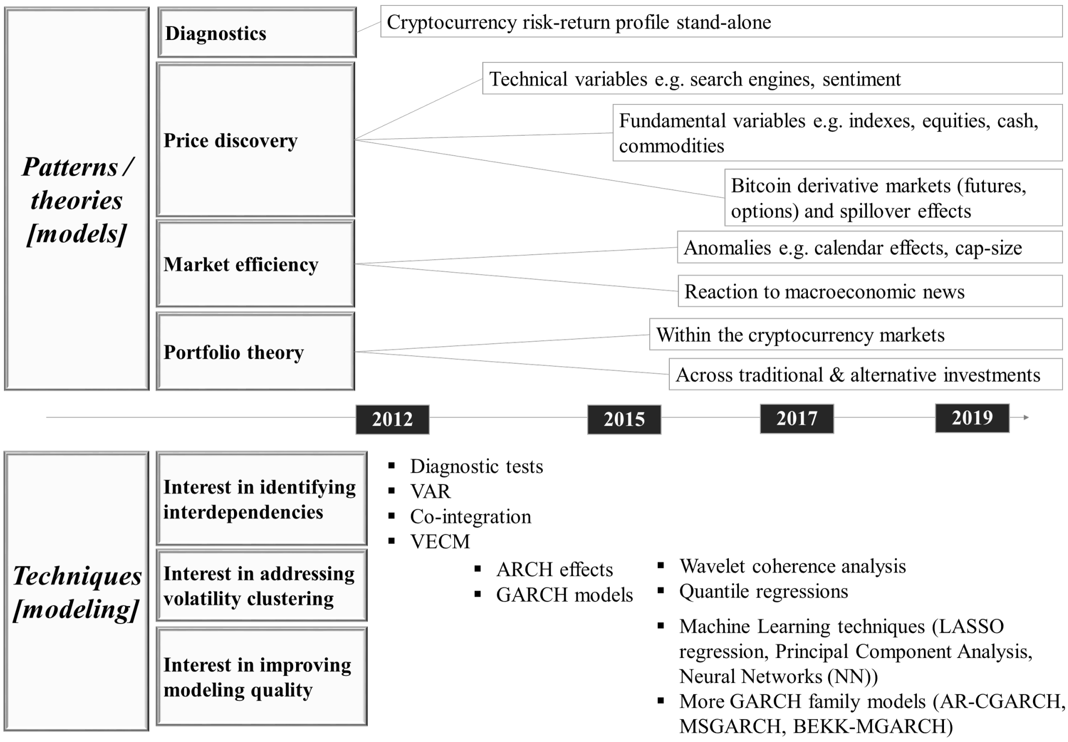
In studying peers behavior scholars have paid more attention to the cost and benefits trade-offs for using blockchain as payment system. Iwamura et al. (2014) and Hayes (2015) elaborate upon the behavior of miners as a critical point for Bitcoin's network success and argue that there are facing a typical optimization problem with the objective function being the net benefit/return and the constraint being the mining cost which include electricity for Central Processing Unit (CPU) etc. Their main concern is that if Bitcoin's price plunges, then the net benefit/return ratio plunges for that the benefit is proportional to Bitcoin price which may induce miners' market exit, thus blockchain's (mining) sustainability is at risk. The role of network effects and switching cost is suggested by Luther (2016). Eyal & Sirer (2018) reject the celebrated ("conventional wisdom" in their own words) stability hypothesis that Bitcoin protocol is incentive-compatible and raise the matter of insecurity against colluding minority mining groups.

Chiu & Koeppl (2017) estimate welfare loss in Bitcoin in relation to energy consumption concluding that the introduction of alternative consensus algorithm protocols like Proof-of-Stake replacing Bitcoin's Proof-of-Work can substantially lower this negative externality. Recently, Easley et al. (2019) argue the emergence of transactions costs in studying a variety of micro-structure features of blockchain. Transaction costs have long intrigued scholars. Another compelling result is delivered by Budish (2018) whose theoretical inquiry show that blockchain systems end up to collapse and failure because of the majority attack (51 per cent owning the hashrate that is, mining's computing power) in the event of persistent hoarding likely to emerge as agents highly value the *store-of-value* function in Bitcoin akin to precious metals. An empirical investigation of transcation costs was earlier performed by Kim (2017).

Sockin & Xiong (2018) follow the deployment of new blockchain structures and examine the role of information sharing in Initial Coin Offerings (ICO). They identify the possibility of no equilibria resulting to platform failure with single-fee design (running on proof-of-work consensus algorithm) suggesting that traditional funding instrument (Initial Public Offering) or alternative consensus algorithm such as the Proof-of-Stake wherein the issuer may set separate fees can arrive to a unique equilibria due to this flexibility. By the same token, Díaz et al. (2019) parts ways from the usual frameworks of Bitcoin analysis by devising a theoretical setting of utility (and security) cryptocurrencies, thus centrally issued by private entities wherein they apply welfare theorems and discuss the properties of the asymmetric information problem emerged.

The blockchain technical structure called Fork is the result of dispute among peers in Distributed Ledgers and is systematically studied in Biais et al. (2019) who identify the possibility of equilibria in blockchain in the presence of Forks, though leading to

Exhibit 2.4: Evolution of the related asset pricing literature




negative externalities (computing capacity, orphaned blocks and persistent divergence between chains). Another source for the creation of dispute (Forks) alarmed by this study are information delays and software upgrades.

Finally, smart contracts are meticulously examined in Cong & He (2019) who conclude that can mitigate informational asymmetry and improve welfare and consumer surplus.

### 2.3.2 Survey of the literature on cryptocurrency asset pricing

In this strand, two broad approaches are employed in dealing with seven categorical research interests. In “patterns / models”, scholars propose theoretical models derived from the finance literature aiming to identify relationships between key variables about cryptocurrencies’ trading activity. In “techniques”, scholars propose statistical and econometric techniques to improve the quality of study of the aforementioned patterns/models. Both strands employ empirical methods. The schematic illustration is as follows.

### Patterns (models)

First, it is reasonable to expect that at the very beginning typical diagnostic time-series analysis tests captured research interest in analyzing cryptocurrency data. Methodological framework for the statistical analyses of cryptocurrencies' time-series are sufficently documented in Nadarajah & Chu (2017). Since the very early years, there has been a clear consensus in the literature that there is strong empirical evidence on the speculative nature of Bitcoin for that the means of payment motive has been utterly refuted (Yermack, 2013; Brito & Castillo, 2013; Bouoiyour et al., 2014; Kristoufek, 2015; Glaser et al., 2014). Later on, similar studies on exploring long memory effects in the volatility measure are conducted on other popular cryptocurrencies as they continue to come out (Chan et al., 2017; Baur & Dimpfl, 2018; Phillip et al., 2018; Caporale & Zekokh, 2019; Phillip et al., 2019). Periodically, empirical evidence of speculative bubbles and explosive behaviors in Bitcoin and selected Altcoins (cryptocurrencies alternative, yet similar to Bitcoin) are found as in Cheah & Fry (2015), Fry & Cheah (2016), Gkillas & Katsiampa (2018), Hafner (2018) and Cagli (2019).

Second, we were able track many studies that apply price discovery frameworks. A variety of pricing models has been suggested and examined with the intention of understanding what drives market prices. But, the difficulty in Bitcoin was to identify the suitability of these models. A first attempt was to relate Bitcoin price with non-financial factors, thus outside the scope of traditional fundamental pricing models. Glaser et al. (2014) use qualitative proxies based on revealed preferences (digital data from search engines such as Google trends) to examine and find that Bitcoin's price has one-sided bias towards positive publicly disclosed news. In a similar in methodological context study, Garcia et al. (2014) identify positive interdependence between social media use and Bitcoin's user base.

In terms of the price discovery objectives, we recognized many, yet unsuccessful empirical exercises to fit cryptocurrencies in traditional pricing models. Kristoufek (2013) and Ciaian et al. (2016) being both skeptical agree that pricing cryptocurrencies as traditioanl assets is not advisable since interest rates for digital currencies are absent which actually entails that speculative profits can only be made from price variation. Claims for the existence of dependencies between (a) cryptocurrencies and foreign exchange markets (Baumöhl, 2019) and (b) equities and commodities (van Wijk, 2013; Kristoufek, 2015; Dyhrberg, 2016a; Corbet et al., 2018; Bouri et al., 2019) have been periodically submitted. For Urquhart (2018) realized volatility and volume are significant fundamentals that cause investor attention. In the same spirit, Wei (2018b) utilizes a large dataset comprising 456 cryptocurrencies to demonstrate the negative relationship between liquidity and market inefficiency (as measured by return predictability). Linkage between Bitcoin and the stablecoin named USDTether in the form of unusual trading activity is investigated by Griffin & Shams (2018). The study implies that this token drives the price of Bitcoin during the 2017 boom and attribute the findings of asymmetric autocorroletions to the fact that the token turns under-collaterized before month-ends (insufficient reserves).

Nonetheless, the most recent attempt in this strand of literature is the introduction of Bitcoin futures and options following the launch of the first organized derivative markets in late 2017. Chen et al. (2018) study implied liquidity as well as Madan et al. (2019). Alexander et al. (2019) use minute-by-minute data to assert that derivative markets lead spot prices. Other works attempt to discover spillover effects, yet between pairs of cryptocurrencies in the spot markets as in Katsiampa et al. (2019).

Third, market efficiency and the identification of empirical anomalies have greatly motivated researchers. By analyzing Bitcoin returns, Urquhart (2016) rejects the weak-form efficient market hypothesis in a first elementary exercise in this field. The exploration of calendar effects first in Bitcoin (Katsiampa, 2017) and subsequently to other cryptocurrencies (Caporale & Plastun, 2018; Kaiser, 2019) have resulted to inconclusive findings on accounts of different modeling techniques and periods selected. Different reactions following the disclosure of macroeconomic news between Bitcoin and gold is found in the event study of Al-Khazali et al. (2018). The size-effect is explored in Shen et al. (2019) who prefer the three-factor pricing model over the CAPM model to diagnose that small market-cap cryptocurrencies tend to yield higher returns. The semi-strong efficiency hypothesis, the examination of Bitcoin returns under the examination of event-study methodology with respect to macroeconomic news and more interestingly to own (Bitcoin) events is introduced by Vidal-Tomás & Ibañez (2018). A very recent study (Cahill et al., 2020) proposes a fresh framework for event studies. Cahill et al. (2020) investigate the causation between abnormal returns of listed US equities (differentiating between blockchain-related firms and others) to speculative and non-speculative announcements. Even though researchers acknowledge the possibility of mi-specification error in their model, they arrive to an interesting interpretation of their results to support that investors may confuse Bitcoin asset performance with the blockchain technology *per se* as indicators of future success.

Four, portfolio theory has entered the cryptocurrencies' research landscape motivated by the potential patterns for reducing risk either for purpose of either (a) hedging, thus looking at negative correlations with other assets and taking offset positions or (b) diversification, thus looking at zero correlations with other assets and amplifying the open positions in the portfolio. Empirical inquiries within the cryptocurrency markets are found in El Alaoui et al. (2018); Griffin & Shams (2018); Zhang et al. (2018); Liu (2019) whereas portfolios blending cryptocurrencies with traditional investments (primarily currencies and equities) as well as with alternative investments are found in Corbet et al. (2018); Kajtazi & Moro (2019); Sovbetov (2018). This demarcation in portfolio construction is exemplified in Borri (2019) who finds that the five major cryptocurrencies within the crypto-market are highly exposed to tail-risk while they are not in portfolios to include traditional assets due to hedging capabilities. This was also evident in the study of Dyhrberg (2016b) who calls Bitcoin "virtual gold" for its akin ability with gold to efficiently hedge against US equities and the US dollar in the short-run as well as in Osterrieder & Lorenz (2017). Latest engagements in portfolio pricing refer to studies that aim at constructing cryptocurrency Indexes (Trimborn & Härdle, 2018) to better assess these growing alternative markets (Chuen et al., 2017) highlighted by the constant diffusion of diverse investment crypto-assets.

### Techniques (modeling)

From very early, researchers treated Bitcoin as typical financial asset that requires the employment of time-series analysis methodology. Buchholz, Delaney, Warren, & Parker (2012), Kristoufek (2013) and Glaser et al. (2014) where the first to detect auto-correlation (correlogram, Breusch-Godfrey tests) and non-stationarity (KPSS tests, Dickey-Fuller unit root tests) to arrive to the conclusion that Bitcoin is prone to temporal periods of structural volatility that is, conditional heteroskedasticity hinting at the employment of naive ARCH and GARCH models. The identified non-stationarity in Bitcoin exchange rate and other blockchain variables, made scholars to apply co-integration tests in modeling long-term relationships. In doing so, Error Correction Models (ECM) were developed (van Wijk, 2013; Garcia et al., 2014; Bartos et al., 2015; Ciaian et al., 2016). Also, Vector Autoregression models (VAR) as in Buchholz, Delaney, & Warren (2012) and analysis of causality (Granger methods) as in Gandal & Halaburda (2014) were common in the mist of early dawn of this research field.

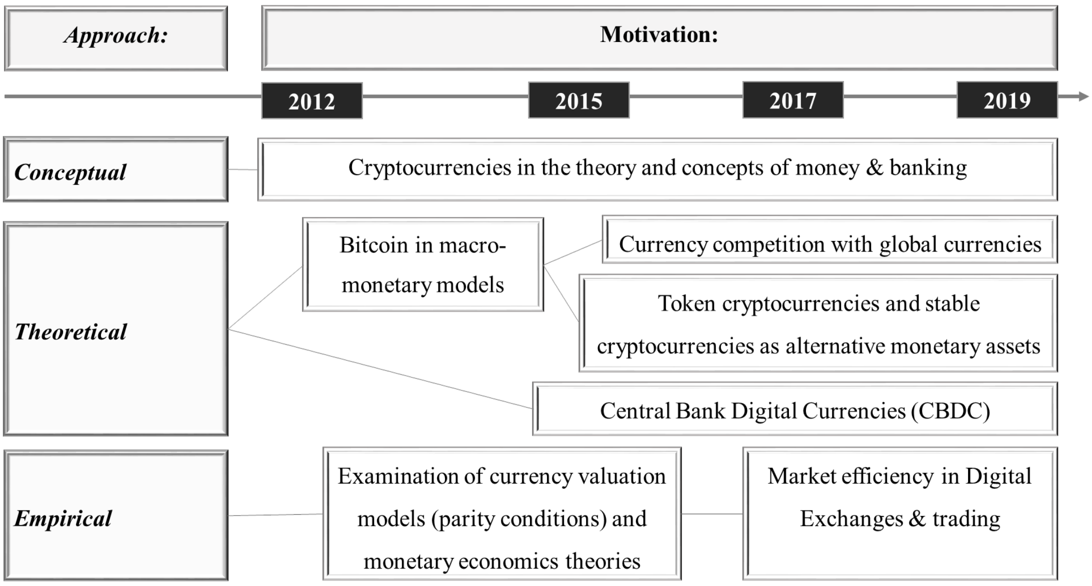
As time-varying volatility continue to persist, more complex GARCH family models were proposed. Katsiampa (2017), Chu et al. (2017) and Caporale et al. (2018) offer comparisons of GARCH specifications with regards to goodness-of-fit. A few years later, such single-regime GARCH models were outperformed by even more complex specifications like the Markov-switching GARCH (MSGARCH) and the use of Bayesian approach as in Ardia et al. (2019).

The last wave of modeling include sophisticated Machine Learning (ML) techniques with a view to improve modeling quality. Supervised ML techniques are used by McNally et al. (2018) and Panagiotidis et al. (2018). By way of example, the latter prefer LASSO regression analysis (least absolute shrinkage and selection operator) to improve prediction accuracy. Lastly, in a very unpopular approach contrary to the complexity of the previously mentioned, Detzel et al. (2018) explore trading strategies using traditional techniques from the arsenal of technical analysis tools.

### 2.3.3 Survey of the literature on cryptocurrency applications on the macro-banking level

This part of the literature encompasses studies that are concerned with (a) conceptual, (b) theoretical and (c) empirical issues. The first contributes classifications, taxonomy and overall understanding of the money and banking functioning. The second specifies theoretical models in examining equilibria in supply and demand for such money balances. The third furnishes empirical evidences from applied cases. The evolution of the related literature is displayed in the figure below.

Exhibit 2.5: Evolution of the related macro-banking literature




#### Conceptual: money & banking

First and foremost, scholars endeavor to address crypto-currencies' presence within the role of money and banking. Buchholz, Delaney, Warren, & Parker (2012) align with

Barber et al. (2012) who claim that Bitcoin is not commodity-based currency opposing to G. Selgin (2012) who considers Bitcoin as "*quasi-commodity*" currency. A year later, G. Selgin (2013) re-establishes this term as "*synthetic commodity money*" coining an interesting new taxonomy of base-money. Others like Kroll et al. (2013) have termed Bitcoin "a decentralized electronic fiat currency". From there, Vitari (2014) and Peters et al. (2015) attempt to formally place cryptocurrencies into a general taxonomy of electronic money on the basis of specific criteria. More questions are set forth by Weber (2014) from the social viewpoint, (Smit et al., 2016) from the institutional viewpoint and Ammous (2018) from the monetary viewpoint who all struggle to convince themselves to accept Bitcoin as part of the monetary system. Even more reluctant to this idea is Danielsson (2019), but only pays attention to Bitcoin. The nature of possible interaction of cryptocurrencies with the conventional financial system is broadly discussed in Böhme et al. (2015).

It is Y. Yamaguchi & Yamaguchi (2016), however, who deliver the most meticulous approach in this inquiry. The authors suggests five kinds of media of exchange i.e. non-metal commodities, metal coinage, paper notes, electronic card and substitutes and blockchain which may fall into two main categories namely public (issued by the consent of people where money is legal tender) and debt money (issued privately where money can be legal tender of functional-money, thus at interest). In addition, they use the metaphor of Bitcoin looked at as ingots, a term coined by E. F. Fama (1980), if turned into functional-money. Recently, scholars try to categorize differences between cryptocurrencies as the market grows in size. Ankenbrand & Bieri (2018) proposes different asset classes and indexes.

We don't leave out of this macro consideration studies from specialized background as the ine by Evans (2015) who analyzes Bitcoin from the Islamic Finance standpoint of view. The study concludes that Bitcoin conforms with Islamic requirements as it incorporates three fundamental principles namely (a) the prohibition of *riba* (that is, usury) and (b) of *maslaha* (that is, social benefits of positive externalities) and mutual risk-sharing (as opposed to risk-shifting).

### Theoretical: macro-monetary

With regards to monetary modeling, the digital challenge to General equilibrium models is posed by Verme & Benavides (2013) who propose refining of what they refer to as "decontaminated physical environments of typical Arrow-Debreu economies". Since 2014, a growing body of the literature studies the impact of the constant diffusion of more and more cryptocurrencies. Iwamura et al. (2014) welcomes this as "*a healthy sing of* *currency competition à la Hayek*" who argued that price mechanism in pursue for profit would operate in such a way that money retains its value. In that respect, Ianiro (2014) attempts to models cryptocurrency in a CIA (Cash-in-advance) optimizing framework aiming to examine how competition improves traditional currencies' effectiveness. Iwamura et al. (2014) in examining the potential of Bitcoin to compete with Central Banks, suggest an embedded monetary policy (thus, a built-in revaluation rule for exchange rate) so as to deal with cryptocurrencies' fundamental problem of price instability (deflation). This proposal implies the use of expected inflation but does not explain how this can be framed within the Distributed Ledgers ecosystem. In any case, the study put forth the idea of cryptographic prudential monetary policies.

Following the first peak in Bitcoin trading history in early 2014, the proliferation of this "apolitical" payment system wherein new monetary assets are created in accordance with a predetermined supply schedule intrigued scholars to research interactions with the real economy. For Hendrickson et al. (2016) and Hendrickson & Luther (2017), the employment of monetary models with endogenous matching and random consumption preferences is capable of identifying the theoretical conditions under which government policy might ban or at least discourage the use of bitcoins.

In close spirit, Garratt & Wallace (2018), Zhu & Hendry (2018), Kang & Lee (2018), Biais et al. (2018), M. Fama et al. (2019) and Huberman et al. (2019) introduced new varieties and from there Schilling & Uhlig (2019) extended to arrive to a fundamental pricing formula for Bitcoin claiming that its high volatility does not invalidate the medium-of-exchange function. Benigno et al. (2019) set up a model with two-country economies (and two national currencies) and a global cryptocurrency to conclude that the latter leaves national considerations by central banking with limited choices. Common factor of this strand of money and banking literature with regards to cryptocurrencies is that only focus on Bitcoin and alike, thus decentralized cryptocurrencies whose supply is characterized by a deterministic (exogenous), weakly increasing and concave function of time. One interesting, yet new contribution is the employment of cryptocurrencies to Dynamic stochastic general equilibrium (DSGE) models attempted by Asimakopoulos et al. (2019).

In contrast, little has been said about the arrival of centralized token cryptocurrencies publicly issued by real businesses as far as their possible monetary implications are concerned challenging fundamental concepts of traditional currency and banking (Díaz et al., 2019). Senner & Sornette (2019) theoretically analyze the inherent monetary design of cryptocurrencies to conclude that are built on outdated monetarist theories. But this study focus on Algorithmic assets with pre-determined supply path, alike Bitcoin, failing to extend the analysis to Tokens (IOU) assets. We believe that this area of money and banking research could become of great interest in the near future.

Of course, monetary models for stabilizing the price of cryptocurrencies have been developed as in Mainelli et al. (2019). Increasing attention gain lately the new breed of cryptocurrencies that are pegged to an anchor and referred to as "stablecoins" (Caginalp, 2018). The examination of *prudential* stabilization mechanism embedded in algorithmic (decentralized) cryptocurrencies is a new promising area of research. Mita et al. (2019) offers a taxonomy on the basis of the collaterized asset and Pernice et al. (2019) broadens the analysis to relate cryptocurrencies with traditional exchange rate arrangements. A valuation framework to explain exchange rate variation can be found in Bolt & Van Oordt (2016) who suggest three components i.e. current value of transactions, decision and expectations of forward-looking investors and merchant acceptance. A more complex strand of literature for that is unclear in orientation and affinity with cryptocurrencies as earlier mentioned relates to Central Banks. In 2015, Barrdear & Kumhof (2016) examine for the first time the potential of Central Bank issued Digital Currencies (named CBDC)[12] borrowing some features and concepts from the Distributed Ledgers technology. In the literature, CBDC are currently viewed as alternative (additional) monetary policy instrument for the sovereign currency in tandem with reserves requirements, base interest rate and open market operations (Meaning et al., 2018). In an akin manner, the launch of similar central bank digital currencies has been proposed in the literature (Bech & Garratt, 2017). Research now is driven by such possible applications, thus currencies of digital form issued by monetary authorities e.g. FEDcoin in Koning (2016), even international organization (e.g IMF) without public ledgers.

### Empirical: macro-finance

In the empirical set, until now studies have centered their attention to competition across cryptocurrencies but also across digital exchanges for that their no unique closing daily price due to absence of a centeralized exchange organization. For Gandal & Halaburda (2014), according "*network effects*" literature postulates that convergence towards one dominant-player both in (intra)competition within currencies as well as in (inter)competition across market exchanges sphere is most likely. Evidently, this was happening with Bitcoin until mid-2017, yet the trend now is declining. That year, Gandal et al. (2018) are concerned by the recent bankruptcy of Mt.Gox exchange, one of the leading market makers at that time (as wallets were hacked and bitcoins were lost) and

[12]In literature, this work relates to "Why does Money affect output" (Blachand, 1990).

investigate possibly suspicious trading via price manipulation to have boasted Bitcoin price.

Concurrently, the need to empirically examine the integration of the market leader (Bitcoin) with the real economy surfaced. The purchasing power parity theory is tested by Tasca & de Roure (2014) who compare physical and digital/virtual market places of same commodities, though of controversial economic utility (drugs) to draw the conclusion that the latter due to the use of Bitcoin as media of exchange "*change the speed of information dissipation*". It is, however, true that cryptocurrencies have been widely associated with easing illegal economic transactions (Brito & Castillo, 2013; Foley et al., 2019). Dyhrberg et al. (2018) explore the market microstructure of Bitcoin through high frequency intraday data to argue that most trading activity in terms of high volatility and low spreads takes place during US market trading hours while transaction size profile fits better to retail rather to institutional investors.

## 2.4 Conclusion & future research

The stated aim of this paper was to survey the events, contextual factors, research methods and findings that are associated with the Distributed Ledgers literature still in its infancy. Cryptocurrencies and blockchain appeared in 2009 and are currently at the core of many of the emerging technologies that are expected to transform the way the exchange of economic information takes place in the economy. Granted, then, that this new literature will continue to grow, what is to be expected from future research? It seems probable that this will relate to the three domains that this survey draw upon the status of current research.

It is true, of course, that research will depend in the main, on developing and testing asset-pricing models for cryptocurrencies as alternative assets. The prevalence of the idea, however, that Stable cryptocurrencies and Token (IOU) cryptocurrencies, taken in their macro-monetary context, may challenge traditional commercial banking operations such as short-term lines of credit and in turn, being able to circulate in tandem with traditional central banking currencies, which continue to rest with the unit of account and store of value functions, is anticipated to gain significant interest. Also, the fact that blockchain applications are being examined by various industries, the sustainability issue will call for exploring more carefully the potential limitations in such peer-to-peer systems. In the most fundamental sense, suffice to say that rarely scientific pluralism could partner in such persuasive way as in this interdisciplinary and multidisciplinary literature that this survey aimed at bringing to the limelight.

# Chapter 3

# An inquiry into cryptocurrencies as Alternative Banking

This paper aims at positioning cryptocurrencies in the history and theory of exchange. This approach will have the effect of bringing cryptocurrencies as closely as possible to the definitions and operations of central and commercial banking. By mastering all varieties of cryptocurrencies (algorithmic, tokens, stablecoins) with respect to their monetary foundations, we envisage how competition with traditional banking in the money markets is likely to occur. The absence of inside money, however, due to lack of portfolio management activities impedes cryptocurrencies' penetration into capital markets where the banking sector continues to prevail.

## 3.1 Introduction

Without a doubt, since the late 20th century the spread of technological innovation in financial markets worldwide have irrevocably restyled transactions vis-à-vis the availability in forms of payments and media for exchanging wealth. The latest diffusion referred to as cryptocurrencies has arguably disrupted International Finance & Banking towards *denationalization of money* (Hayek, 1976) and dims new light on an aged matter of Political Economy going back at least to the eminent Ancient Greek philosopher Diogenes of Sinope[1].

[1]Famed as one of the founders of Cynic philosophy he is also known as Diogenes the Cynic. (4th c. BCE). There are conflicting historical accounts over the exact accusation i.e. adulteration or defacing or debasement of the local currency (Navia, 1996) that possibly led to his own exile from Sinope. His alleged act has been viewed political resolving to back out of greedy banking

The fact that the definition of Bitcoin and all of its offspring as cryptocurrencies, a term which its creator never used in the notorious Bitcoin paper (Nakamoto, 2008), underlies traditional economic concepts, imports into it a great element of ambiguity. Our motivation is to respond to this inadequacy by carefully positioning cryptocurrencies in the history and theory of exchange. The introduction of the concepts of money and banking along the history of economic thought, as in this paper, will have the effect of bringing all kinds of cryptocurrencies as closely as possible to the definitions and operations of central and commercial banking. This is critical for backing cryptocurrencies' claim as alternative monetary assets. The main research question is simple. Are all varieties of cryptocurrencies another sort of monetary exchange in addition to the traditional ones?

Following a systematic methodological inquiry, we conclude how each cryptocurrency asset class introduces competition to different markets on the basis of which function of money is essentially served. Algorithmic coins to commodities and durable assets functioning as store of value. Tokens (IOU) issued by private entities to fiat-money and fiduciary-money (promissory notes) functioning as deferred payments. This category may play a significant role as a substitute to commercial banking's checking accounts and pledged asset lines of credit. Stablecoins to electronic banks functioning as media of exchange. Notably, traditional currencies are still of the greatest value and importance to the real economy and surprisingly to cryptocurrency ecosystems for that they convey the intelligence of the prevailing numéraire. That is, the unit of account.

The remaining of this paper is organized as follows. Section 2 offers the necessary literature grounding prior to the subsequent monetary analyses in sections 3 and 4. Section 5 discusses macroeconomic implications. The last section concludes.

## 3.2 Background

This section cites the relevant literature accompanied by a few definitions.

### 3.2.1 Related literature

While the trading behavior of cryptocurrencies from the finance standpoint of view still leads this area of research, there is a new and growing body of literature on their mon-

for a studentship with Antisthenes in Athens only to end up a penniless philosopher. Hayek (1976) writes that he called political money as "legislators' game of dice" to communicate that the governments abuse money and orderly the "confidence and belief of their subjects" (Smith, 1776) as famously put it.

etary analysis as varieties of cryptocurrencies continue to grow. Thus, the monetary analysis of all kinds of cryptocurrencies and the establishment of appropriate definitions with respect to their monetary arrangements are the main gaps in our existing knowledge of this financial technology which it will be necessary to fill. Related works on the monetary nature of cryptocurrencies consists of (a) conceptual, (b) theoretical and (c) empirical studies. This paper contributes across the first. We offer consistent definitions whereby all cryptocurrencies partition into partricular segments, and in turn fit in the history of exchange. This approach is related, yet complementary to the works of Buchholz, Delaney, Warren, & Parker (2012), Barber et al. (2012), G. Selgin (2013), Kroll et al. (2013) who focus on Bitcoin. Our money and banking methodology is aligned with current theoretical workings in examing the monetary arrangements of cryptocurrencies in general (Ammous, 2018; M. Fama et al., 2019; Fantacci, 2019) as well as of Stablecoins in particular as in Calcaterra et al. (2019); Moin et al. (2019); Nakavachara et al. (2019); Benigno (2019). We extend by introducing more carefully the traditional operations of central and commercial banking in an attempt to clearly envisage how the varieties of cryptocurrencies can further penetrate into the financial markets.

### 3.2.2 The connotation of the numéraire

The idea that we will shortly delve into the ambiguity of money requires a proper conceptual framework beforehand. An economic phenomenon is understood as the proportional exchange of two values of goods. In a barter economy arises the problem of double-coincidence of wants which the concept of money effectively addresses. Yet, money need to be expressed in a common unit of account called the numéraire.[2] At this point let's recall that currency is not money for that the former essentially represents the latter. Similarly, money is imaginary (unreal) for it merely represents (real) values. In practice, money has been devised *"for the convenience of exchange"* as Nicholas Barbon wrote in his work with the title "A discourse of trade" published in 1690. It bears keeping in mind at the outset, however, that it is from the *peculiarity* of the three fundamental functions of money (Jevons, 1875) i.e (a) unit of account, (b) store of value and (c) means of payment that two other concepts come into being i.e credit and banking and as a consequence a fourth function, that is (d) means for deferred payments. A useful comment at this point. Notice that money has a life cycle whereby these functions need to work in a specific sequence starting from a and ending to c. Some monies reach only

[2]Empirical research on the *numéraire* and money illusion dates back to Irving (1928), Keynes (1936) and recently to Shafir et al. (1997) and Fehr & Tyran (2001) as Reis et al. (2007) inform us.

b, so are only desirable as store of value. For example, precious metals.

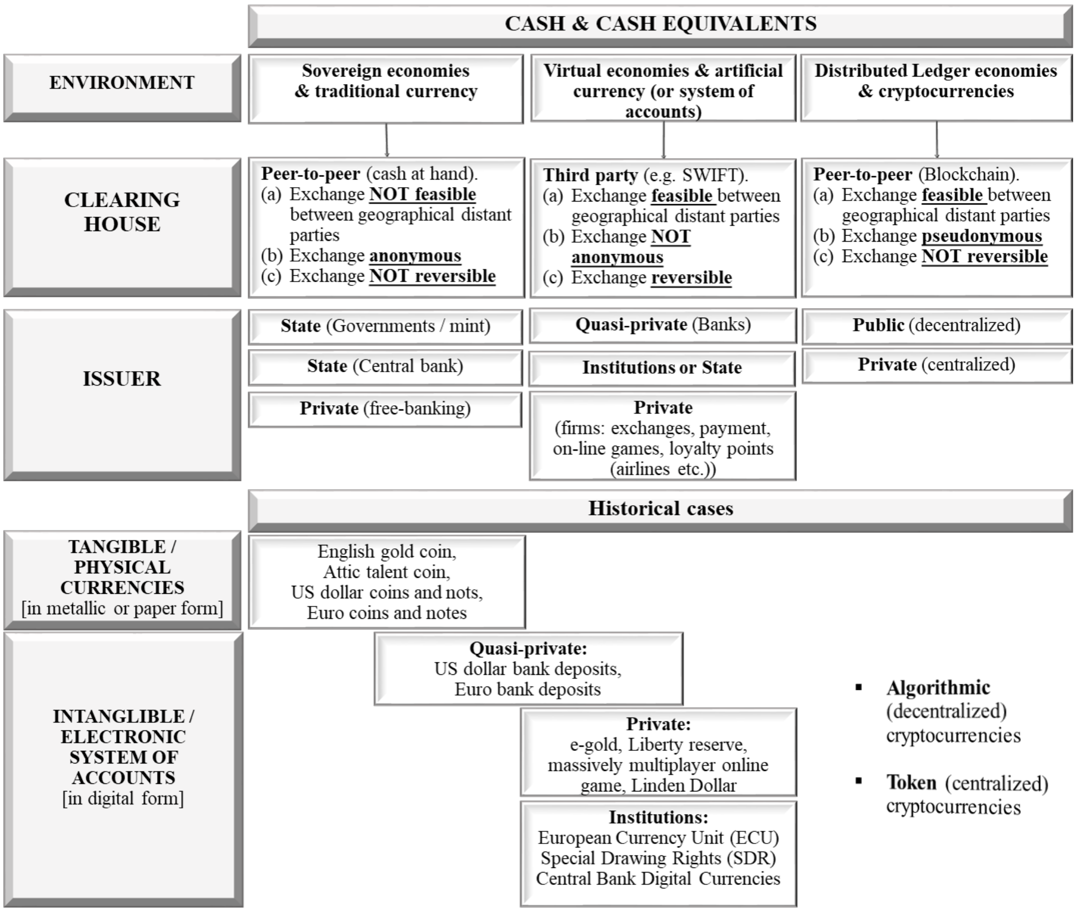
Apparently, money is an asset but determining which assets are money is not ease to point down for that subtly requires subjective judgment. Assets encompass various degrees of liquidity. In finance language, the most liquid is cash and cash equivalents, thus this is the end point in the assets line of the balance sheet. Historically, cash arrives in the physical form of coins or notes. The latter in the electronic form of deposits and it is referred to as cash equivalents for that they substitute coins and notes to which are convertible on demand. This asset class is natural to play another role that of the standard of measure. In that event, these are colloquially called functional currencies. Hence, going all the way backwards to the assets line all previous assets are normally expressed in units of this last class of assets, implicitly a mathematical expression of a fraction. In the nominator are x currency units and in the denominator are y units of the asset j. The nominator has an inherent economic substance for that the x currency units represent the value of one unit of asset j. The higher the nominator the higher the value of the asset j relative to other assets expressed in the same unit of account.

It is well-known that all economic propositions are expressed in relative (monetary) terms because theory of value of money itself is deprived of absolute measures. Absolute measurements did not simply pre-existed even for natural sciences, rather had to be mathematically made them up like the meter and the kilogram. In point of act, the unit of account in Economics is just like numbers in Mathematics, thus protocols constructed by the human mind to enable trade across time and space and simply adopted by societies by *public convention* as Keynes would put it. But talking about the metaphysical world of economic thought, it is thought-provoking whether cryptocurrencies could be fashioned to standard units of measurement of value of money thus invariant in the properties being measured as their protocol guarantees that money demand is not *"conditional on expectations of uncertain future variables"* (Keynes, 1936) such as the opportunity cost of money and inflation.

### 3.2.3 Definitions of currencies

Cryptocurrencies fall under the general research field of exchange. Cash and currency are two terms usually used interchangeably for that they share a common numéraire. In this work, we follow E. F. Fama (1980) convention in distinguishing between currency (physical items of cash) and system of accounts (electronic items of cash equivalents) for the exchange of wealth. Having said that, we formalize this approach to disclose the three different environments of monetary exchange, thus excluding barter exchange (goods for goods). The next figure illustrates the literature's boarders.

Exhibit 3.1: Depiction of the related literature milieu




First, there are (i) sovereign economies where the main body of economic research on money and banking is found. Then, there are (ii) virtual economies and electronic systems of exchange. First and foremost, these include non-physical currencies like commercial banking's deposits. At this point, we must guard against a misconception. The previous implies that, at least in theory, by providing not homogeneous portfolio assets against which their depositors can hold claims (E. F. Fama, 1980) every bank issues its own currency. While banks are involved in the process by which a pure nominal commodity is made to play the role of the numéraire in a monetary system (E. F. Fama, 1980), they are unable to establish their own money supply. Thus, "bank deposits" have no meaning until we have specified some standard of measure imposed by a sovereign authority. Hence, (heterogeneous) bank deposits are hard pegged to central bank's currency. The fact that, given that the banking sector's accounting system of exchange is tacitly integrated with the central bank's currency is the justification for the latter being the functional money in the economy. Granted, then, this market structure, banks add to the property of convertibility their portfolio assets for that are obliged to convert their system of accounts to currency (coins and banknotes) on demand.

In the past, there have been attempts to create distinct system of exchange of electronic nature. From the institutional perspective, examples include European Currency Unit (ECU) and Special Drawing Rigths (SDR) by the International Monetary Fund but these have no interaction with real goods. In close relation there are recent proposals for Central Bank Digital Currencies utilizing the blockchain technology (Barrdear & Kumhof, 2016). From the private perspective, there have been virtual currencies issued by private firms in the 90s which can be regarded as the ancestor of cryptocurrencies. Cases include the issuance of virtual currencies used in massively multiplayer on-line games. Also, private firms accepting commodities (e.g gold) in exchange for the provision of an electronic system of payments corresponding to virtual currencies valued at parity with the functional currency. Finally, since 2009 there have been established (iii) distributed ledger environments in which cryptocurrencies are issued and exchanged.

What differentiates the three exchange environments is the clearing house which settles the transactions. First, in physical currencies, (anonymous) exchange takes place hand by hand also referred to as peer-to-peer, thus no intermediary involved. The drawback is that transactions among geographical distant parties is not feasible. Second, electronic transactions dealt with the latter, though at peer-to-peer exchange expense for that a third party acts as a middleman. Third, distributed ledgers economies and the blockchain allowed for the first time to enjoy peer-to-peer exchange between geographical distant (pseudonymous) parties. We deliberately use the term pseudonymous and not anonymous. Since the public ledger always records the complete history of transactions, anonymity cannot be utterly ensured as in the case of traditional cash (at hand). It is should be pointed out again, however, that only when users transact via the built-in blockchain wallets, and not via digital exchanges transactions are truly pseudonymous.

All said, the significance of cryptocurrencies lies in their hybrid nature combining both (a) cash and (b) cash equivalents for that they can be directly held at hand (without a middleman just like central banks' coins and banknotes) though in electronic form (just like commercial banks' system of accounts). We have established, so far, that electronic currency is the blanket term used to characterize cash (or currencies by convention) in digital form. Moreover, that this terms consists of (a) artificial currencies and (b) cryptocurrencies with an embedded electronic peer-to-peer clearing house.

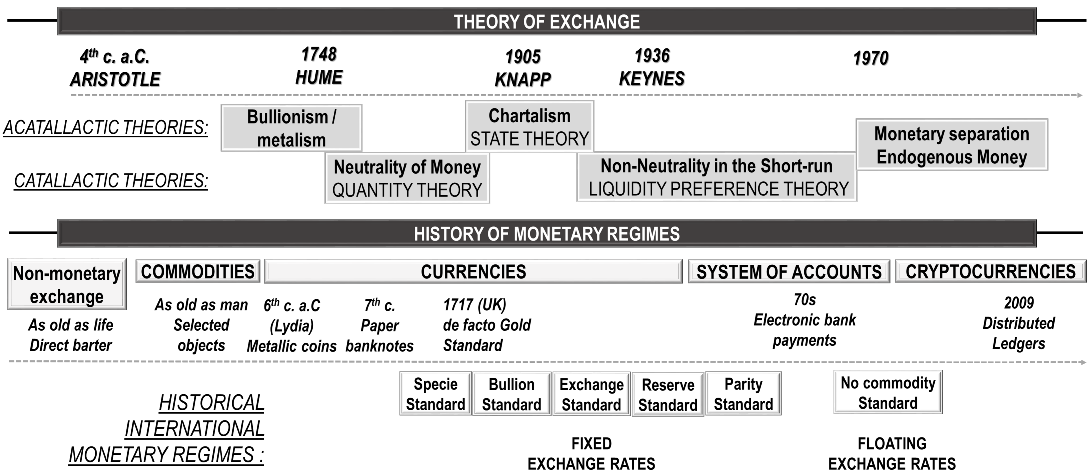
### 3.2.4 A few historical recollections

In human societies, barter transactions were the first form of exchange. But, Davies (2010) sheds light on the actual origins of barter exchange.

> *The history of barter is as old, indeed in some respects very much older, than the recorded history of man himself. The direct exchange of services and resources for mutual advantages is intrinsic to the symbiotic relationships between plants, insects and animals, so that is should be surprising that barter in some form or other is as old as man himself.*

One of the most challenging puzzles in monetary theory is to sufficiently explain the use and holding of money or at least the existence of a positive demand (Brunner & Meltzer, 1971). Non-monetary exchange is related to multiparty barter exchange that is accompanied with computational complexity (Norman, 1987). In monetary exchange literature, an auxiliary unit of account reduces this complexity and the exchange of wealth may arrive in the form of commodity, physical currency and electronic system of accounts. The history of monetary exchange and monetary regimes is intertwined with the history of economic thought on the theory of money. In the most modest attempt, the next figure collects and schematically summarizes the theoretical and practical setting of exchange through ages.

Exhibit 3.2: Evolution of the literature on theory of money & the history of regimes




To put this synthesis of literature review in a nutshell, we draw a contrast between acatallactic and catallactic theories by borrowing the approach contributed by Von Mises & Batson (1953). For the authors the first strand consists of two traditional namely “Mercantilism, Metalism, Bullionism” and “Chartalism” (or the State theory of money by Knapp (1924)). In this frame, acatallactic theories pay only attention to the value-in-use.[3] Contrary, catallactic theories have as common grounding their interest in explaining market prices as they are because they can additionally gauge the value of the purchasing power of money, that is the value-in-exchange. This second strand of the literature constitutes of two well-established traditions namely “Neutrality of money in the Long-Run” postulated by the Quantity Theory of Money (QTM) wherein the price level is a function of money supply i.e $P = f(M)$ and “Non-neutrality in the Short-run” postulated by Keynes's Liquidity Preference Theory (LP) wherein economic activity is subject to the variability of the velocity of money determined by the rate of interest i.e. $Y = V(i)M$. We extend by mentioning the recent debates on “Endogenous money” and “Monetary separation”. At the most general level, endogeneity means the supply of money is not independent of demand. Thus, the level of money is determined by factors in the economy in response to central bank's policy rate of interest. Among the scholars of the heterodox tradition such as Nicholas Kaldor, Paul Davidson, money is seen as credit money. The concept of “monetary separation” is linked to the recent development of a new intellectual trend gaining momentum in monetary theory referred to as “the New Monetary Economics”, a term coined by Hall in 1982 as mentioned by Cowen & Kroszner (1987). The latter explains that the main investigation is the possibility that the unit of account and means of payment, traditionally bundled together in the item called “money”, may become separated. Main contributors are Fischer Black, Eugene Fama and Robert Hall. These, however, include varieties of a common theoretical grounding which has not led so far to a coherent deduction.

We turn, next, at the bottom of the above figure and to the International Finance & Banking setting where exchange rates of currencies are determined. Historically, variations of commodity-based regimes have been mostly adopted. In this respect, Diebold et al. (1991) has distinguished five main Standards namely *specie, bullion, exchange, reserve and parity.* It may be convenient to mention here, in anticipation of the monetary analysis of concepts and theories in cryptocurrencies of the latter part of this work, that, cryptocurrencies are developed upon existing monetary practices and theories.

[3]This theoretical demarcation about the value of assets goes back to Aristotle. See, Palgrave dictionary (1891) vol.1, p.54 in reference to Aristotle's work with the title *Politics.* Aristotle avows “$\delta\iota\tau\tau\eta\ \eta\ \chi\rho\eta\sigma\iota\varsigma\ \epsilon\sigma\tau\iota\nu$”, thus *“value possessed by anything in use and its value in exchange”.*

## 3.3 Types of exchange in cryptocurrencies

In the pre-cryptocurrencies literature, Birch & McEvoy (1997) in a very early attempt deliver standards to distinguish between physical and digital items while H. Yamaguchi (2004) pinpoints the attribute of exchangeability of virtual currencies to endorse their definition as real currencies. In cryptocurrencies era, Bitcoin has monopolized the interest, so far, in this conceptual method of monetary analysis. G. Selgin (2013) characterizes Bitcoin as *synthetic commodity money*, thus it has no monetary use value but it is absolutely scarce. This taxonomy on base-money is grounded on these two criteria. Under this two-by-two matrix framework, the types of money are commodity, fiat, synthetic-commodity and "Coase durables". With the latter, G. Selgin (2012) praises Ronald Coase's conjecture in monopoly theory and the situation of "durable goods" (Coase, 1972). Our intention is to widen this analysis to include all kinds of cryptocurrencies.

In large part, the work of classifying cryptocurrencies follows a general philosophy of revisiting existing definitions, types and taxonomy found throughout the history of currencies and monies (Gurley & Shaw, 1960). Comparisons with these sorts will be provided throughout this section. As a starting point, we put forth a taxonomy of all possible cryptocurrencies' asset classes where definitions are clear cut. The next division into categories will be subsequently further dis-aggregated and interpreted.

1. Bitcoin and Altcoins (alternative to Bitcoin cryptocurrency) alike which follow quantity rules for that they money supply is restricted (programmed) to grow at an increasing but decreasing rate.

2. Altchains also follow the same quantity rule, yet are alternative to the Bitcoin blockchain blueprint wherein decentralized applications (dApps) are developed,

3. Utility Tokens are issued by private firms in the form of advances for real goods, thus imply settlement of outstanding invoices when redeemed.

4. Smart Tokens are related to Stablecoins or to virtual applications where no services are charged by a third party.

5. Cryptocurrencies in steady-state intended to be either (a) Stable in terms of the exchange rate (mostly available today) referred to as cryptocurrencies under price-rules (or Stablecoins) or (b) constant in purchasing power referred to as Quota cryptocurrencies.

The first two categories are considered Algorithmic coins (decentralized) while the next two Token cryptocurrencies (centralized). The last category can be both.

### 3.3.1 Barter-money, currency or system of accounts?

The historical iteration of methods for exchanging wealth in social history as illustrated in the previous figure is articulated below.

[A] As old as life has been non-monetary exchange (no barter-money) or pure barter, thus (i) units of good A for units of good B and (ii) units of good B units of goods C.

[B] As old as man has been specie exchange via barter-money which comes in the form of an object that is either (a) producible (e.g cigarettes) in industry or (b) non-producible found in nature (e.g precious metals and natural resources). For example, (i) units of good B are exchanged for units of good A and (ii) units of good C are exchange for units of good A. The direct exchange of B and C is made redundant.

[C] Since the 6th century a.C. has been currency exchange via a physical medium in the form of metallic coins and banknotes.

[D] Since the 20th century has been available systems of accounts in electronic forms. As explained earlier, these bear an essential traditional linkage with currency money to which is convertible apart from the case of credit (non-convertible) banking money. Such system operates via debits and credits, subtly not requiring any physical media of exchange, thus the concept of money. For E. F. Fama (1980) the concept of money is only innate in (commodity and fiduciary) currencies. An exhaustive elaboration on this is made by Von Mises & Batson (1953).

Davies (2010) refers to the first method as direct exchange while to the others as indirect or immediate reciprocal exchange. The second method, thus exchange with barter-money (species) as media of exchange is close to direct exchange, only that in the former there is a persistence towards specific (like A in the above example) objects rather to direct (goods-for-goods) exchange as in the latter. Among the objects whose intrinsic value (value-in-use) has subtly served as barter-money include precious metals (gold, diamond), leather, Ricardo's corn model, even cigarettes in Prisoner of War Camps (Radford, 1945).

Letting barter variants aside, traditional monetary exchange can therefore be conducted via the last two methods i.e currency and system of accounts. As already remarked, the latter resolved the impediment of geographical distant transactions, though at the anonymity expense. Cryptocurrencies straddle the margins between these concepts, the hybrid of hybrid among monetary assets for that combine distinct properties from all. And our reason for supposing that cryptocurrencies are a new hybrid form of monetary exchange arises from the fact that, broadly speaking, distributed ledgers play the role of (a) distributed payment institutions allowing distant transactions as in commercial banking's systems of accounts, (b) distributed cash allowing direct peer-to-peer, thus close to anonymous transactions as in currencies and (c) barter-money alike via durable and storable commodities. Cryptocurrencies feature all three methods of indirect (monetary) exchange.

- Algorithmic cryptocurrencies which follow quantity rules match with barter-money (specie). This is the case of Bitcoin and, therefore, it bears resemblance with durable commodities not subject to depletion such a precious metals. It should be clear that Bitcoin is not a currency under the Gold Standard like the gold pound. Bitcoin is a digital commodity, thus represents a precious (digital) metal itself using its own standard of measure. Each bitcoin is divisible to the 8th decimal place and, therefore, each unit of bitcoin, or 0.00000001 bitcoin, is called satoshi.

- All other cryptocurrencies match with currency issued by a banking authority. Though, accompanied with an embedded electronic system of accounts similar to present-day commercial banking. In addition, this can allow for pseudo-anonymous transactions.

### 3.3.2 Commodity-money, fiat-money, fiduciary-money or bank-money?

Collected from the history of non-barter exchange and corresponding to their monetary perspective, all cryptocurrencies fall into the major types of money. First, commodity-based backed by scarce natural resources that humans use to sustain life and foster economic activities. Traditionally, issuers of commodity money is nature and, of course the State or at least a delegated Institution. The latter is required to ensure the qualities of the good which needs to be non-producible such as metallic. Decentralized cryptocurrencies with a pre-determined supply growth rate mimicking precious metals bear resemblance to pure commodity-money.

Second, fiat-money[4] exhibits no value-in-use but high value-in-exchange. This value is established by a government order. That means, a sovereign authority declares fiat-money to be legal lender and that agents are obliged to accept it at least as a means

[4]The etymology of the word *fiat* derives from the Latin word *fieri*, thus "let it be done", "be done, become into existence".

of payment and unit of account in settling debts. Apparently, as democratic societies advance, it is not reasonable to believe that present-day economies are compelled (forced) to accept only one media of exchange when they are free to decide whatever legal goods wish to produce and consume. They use fiat-money because there is no better substitute. Notice that Tokens, especially Smart Tokens, are very close to the notion of private-fiat for that the algorithm (the digital law) only accepts this as media of exchange in their respective ecosystem. But, Algorithmic cryptocurrencies and traditional central banks' currencies are not alike since the former are not associated (a) with legal tender, neither (b) with term structure of interest rates nor (c) with national trade imbalances, thus have no fundamentals. This can be challenged by Token cryptocurrencies issued by firms subject to fundamentals. Let us define below, then, an akin kind of money.

Third, the originator of fiduciary-money promises to exchange it back for commodity-money (when bank were accepting gold) or fiat money (like modern commercial banks and even firms in the case of corporate bonds) if requested by the bearer. As long as bearers are confident that this promise will not be broken, these promissory notes can efficiently circulate. Traditionally, the State monopolies fiduciary money issuance via delegated institutional bodies. The backability of this money derives from acceptance for future taxes. And, citizens trust their State. Since, taxes have been in existence and continue to be so as long as organized societies exist, taxes is an ideal deferred expense to affix to fiduciary-money. While the distinction between fiat-money and fiduciary-money is not important for the State, it is the definition of the latter that tells us how non-state money-issuance can be possible.

Until today, the enterprise world has been unable to see wide acceptance of private-money in the form of firms' "promissory notes". This happens (a) due to lack of an accounting system enabling geographical distant transactions and marketability (easy to transfer to another person), (b) the uncertainty of the *going concern* assumption for the issuer unlike taxation, thus deposits are no homogenoues and (c) the likely tendency of private central banks finding *seignorage* more profitable, thus to hyperinflate as G. A. Selgin & White (1994) point out.[5] To conclude, cryptocurrencies feature all forms of money.

- Algorithmic match with commodity-money. Its value is determined by the value of the underlying asset.

- Tokens match with fiat-money. Perhaps, centralized Utility Tokens cryptocurren-

[5]Competition among government-currencies within an international context is examiend in Kareken & Wallace (1981) and Manuelli & Peck (1990).

cies issued as pre-payments for the financing of a project may challenge how Hayek (1976) envisaged private competition in currency-issuance arguing that the market not only can provide the optimal quantity but also and the appropriate variety of money products such as derivative assets.

- Stable cryptocurrencies match with fiduciary-money. These are claims against deposit institutions that can be used in transactions. In practice, their intrinsic value stems from the convertibility property. In theory, they are convertible to commodity or fiat-money.

Four, there is bank-money (or credit-money) and the fractional reserve system. By definition, banks are given the privilege to issue securities and simultaneously deposits denominated in fiat-money. These are claims against credit institutions which can be converted to fiat-money. This kind of money does not exist in cryptocurrencies.

### 3.3.3 Redeemable, convertible or non-convertible?

It is important to understand that the property of convertibility and redeem-ability is at the heart of this analysis. Redeemed currencies do not require a third party to exercise this option rather the holder can exercise it by herself. This is the case with all cryptocurrencies under quantity rules. Conversely, Stablecoins holding reserves are convertible back to these collateral, thus to some extent are guaranteed. A particular exception is the case of non-collaterized Stablecoins. It remains true, however, that even if commercial banks go bankrupt deposits are partly guaranteed by central banks to be converted back to currency (coins and banknotes). In effect, this is the amount of deposits convertible to outside money locked in banks' vaults. To conclude, cryptocurrencies feature all three kinds of money.

- The bearer of Algorithmic cryptocurrencies can redeem these in an on-chain fashion (thus automatically via smart contracts on the blockchain).

- Tokens are either redeemed (a) on-chain (Smart Tokens) or (b) off-chain (Utility Tokens) for products and services offered by real business entities.

- Stable cryptocurrencies are convertible assets with the exception of non-collaterized Stablecoins.

### 3.3.4 Outside money, and the absence of inside money

Outside money can be thought of as a claim against the issuer. This claim can settle deferred payments for either an asset (commodity) or an expense (fiat). In the case of governments, fiat and fiduciary money means that these are acceptable for future payments. From the private sector viewpoint, it is a net external claim, thus outside enterprise activity for that it is termed outside money (Friedman & Schwartz, 1986). On the contrary, inside money is born from the second function of commercial banking (the first being boookkeeping services). This happens via the issuance of deposits and usage of the proceeds to acquire securities, thus by simultaneously selling bonds and loans to depositors where deposits can take on the characteristics of any form of invested wealth (E. F. Fama, 1980). In this context, inside money is regarded as a financial instrument that synchronously creates an asset (for the bank) and a liability (for the bearer). Note that derivatives such as Collaterized Debt Positions (CDP) offered by commercial banks (e.g in factoring of receivables), investments banks (e.g in margin trading) are not inside money for that the collateral is reserved. This means it is locked and remains idle in exchange for the leverage provided. This is not equivalent to the concept of credit bank money. On account of that, over-collaterized cryptocurrencies (for example the cases of DAI, BitUSD) do not stand for inside money.

The above analysis has been carried on the basis of outside money for that cryptocurrencies, so far, only arrive as outside money. To draw out this point, non-convertible Stablecoins could possibly emerge as inside money in the event of a fractional system where depositors leverage on their deposits. There is no reason in general to suppose that such Distributed Ledger applications can operate in a decentralized manner. It is easy, indeed, to conceive of existing cases, as, for example Centralized Stable Tokens to bolster their position with the creation of inside money. The assumption of portfolio management activities naturally necessitates a private entity to assume risk. Garratt & Wallace (2018) have already characterized bitcoins as outside money. By generalizing their approach, they show the importance of interest-bearing bitcoins for rendering bitcoins' value determinate. This aligns with our analysis about the impact of inside money on cryptocurrencies in its absence.

Perhaps something more important follows from this. Could the lack of competitively produced (interest bearing) deposits as inside-money limit cryptocurrencies' penetration to the capital markets and the economy? There are also other factors, over and above the monetary operation of Token cryptocurrencies just mentioned, and these other factors seem unlikely to change the existing landscape.

For, in the first place, the increase of Token cryptocurrencies will tend, owing to the effect of private outside money being always ready to settle invoices, to continue posing challenges to commercial banking's short-term credit lines. However, it is less likely to expand operations to the issuance of securities in large scale. The central idea of cryptocurrencies is to allow individuals and firms to receive resources (capital denominated in the functional currency and labor supplied by workers) and in exchange pay with privately issued money which is backed to some extent by goods produced by the combination of these two factors. Today, cryptocurrencies lack the second factor. While it is common to receive capital (euro, US dollars) in exchange for a Token, it is still uncommon to receive labor and pay the worker with Tokens.

It is, however, to the general principle of these ecosystem the idea of synergies among different cryptocurrencies. Not far away from the last point, the idea of a decentralized bank in which an algorithm imports centralized Token cryptocurrencies issued by different entities and is capable of generating a single asset is intriguing.

## 3.4 Exchange rate arrangements in cryptocurrencies

Exchange rates are asset prices. Exchange rates determine the price whereby currencies are exchanged usually with the intent to acquire a good sold in units of another currency. In International Finance, the legal distinction between *de jure* and *de facto* arrangements applies. In (Algorithmic) cryptocurrencies, with the exception of Tokens, these two should coincide due to their irreversible programmed supply schedule.[6] To start with, a few historical recollections are pointed out. There are two major iterations of an exchange rate namely (a) fluctuate and (b) targeted not to fluctuate or at least within predetermined close bands. In Distributed Ledgers terminology, we have established that we refer to the former as "cryptocurrencies under quantity rules" and the latter as "cryptocurrencies under price rules". It should be evident from the next analyses that the former follow no-commodity standards while the latter varieties of commodity standards derived from the rich history of international monetary regimes.

' From the different types of exchange rate arrangements, each cryptocurrency category adopts its own standard, keeping in view its economic rationale. By the same token, monetary frameworks include three mutually exclusive targets i.e. (a) supply, (b)

[6]The former refers to the declared arrangement by the issuer whereas the latter to the actually implemented by the latter. These practical concepts are attributed to International Monetary Fund periodic reports (Kokenyne et al., 2009).

change in the price level, thus inflation observed in goods and (c) fixed exchange rate (Mishkin, 1999). To conclude, division of cryptocurrencies on the basis of the selected exchange rate arrangements and monetary framework are summarized below.

- Cryptocurrencies under quantity rules, thus under floating exchange rate regimes implement (a) Money aggregate targeting and (b) Inflation targeting monetary frameworks.

- Cryptocurrencies under price rules, thus under fixed exchange rate regimes implement price targeting frameworks.

### 3.4.1 Floating exchange rate regimes

Floating exchange rate arrangement encompasses two monetary frameworks (or targets) namely monetary supply targeting and inflation targeting. Most cases in cryptocurrencies fall into the first case. By way of example, Bitcoin, Altcoins, Altchains from the decentralized side freely float since their money supply schedule which is predetermined. On the other hand, Tokens under the quantity rule also independently float, but not freely for that the (centralized) issuer may exercise control over the supply. This refers to the practice of reducing supply by permanently withdrawing units ("burning", thus destroying) and in its aftermath boost prices. This strategy is close to equities' treasury stock, thus buying back shares issued with the intention of price appreciation. Interestingly, Algorithmic and Token Quota whose supply expands and contracts are aiming to maintain stability in purchasing power. This asset class is fairly new and not tested. This classification bears further emphasis.

- The monetary framework of Algorithmic coins (Bitcoin, Altcoins, Altchains) and Tokens (Utility and Smart) is money aggregate targeting in which no commodity standard is assumed. The money aggregate of the above mentioned Algorithmic mimics natural resources' supply. While in commodities the "issuer" is the nature itself, in digital commodities the issuer is the algorithm. Put it differently, from the monetary framework perspective, supply follows the k-percent rule attributed to Friedman & Schwartz (1986) who favored for pre-determined (constant, k) rate of increase of the money supply. The intrinsic value of these digital assets stems from the blockchain, that is the embedded distributed payment system. The execution of transactions in their electronic bookkeeping system involves as media of exchange and as the nominal unit of account their built-in asset which is absolutely scarce. Again, it is underscored that these Algorithmic coins do not follow gold standards alike (via free coinage or convertibility) rather represent a digital specie by themselves. Hence, these Algorithmic coins and Tokens are non-convertible (to a particular commodity or cash) but can be redeemed by the bearer for settling payments.

- The monetary framework of Algorithmic and Token Quota is inflation targeting. These can be defined as cryptocurrencies which follow a price-specie standard.[7] Such cryptocurrencies are pegged to a commodity anchor, thus to specific quantities. It is worth adding that in the future we may experience the development of digital assets pegged to quantities of Algorithmic cryptocurrencies say the Bitcoin in an idea very close to the classic Specie Gold Standard. To extend, of course there is the case of price-specie mechanism applied to centralized Tokens in which the underlying is x units of a producible good by a private firm. Given that the cryptocurrency Token is pegged to the quantity of this industrial good, such rare monies grant stable purchasing power to the bearer. By way of example, a private company could issue a Token with which a holder can pay for a good at a price agreed at issuance. This arrangement is closer to the concept of an option contract without expiration. By and large, the pure novelty of this commodity Standard is the implied automaticity and stability resulting to a self-correcting mechanism with little or no intervention. It will be safe to also define these as non-convertible. Instead, the bearer can redeem these for payments.

### 3.4.2 Fixed exchange rate regimes

Cryptocurrencies under price rules follow fixed exchange rate regimes which are implicitly based on more variants of the commodity Standard. In the history of international finance, fixed regimes can be distinguished between hard (or rigid) and soft pegs. Furthermore, the former encompasses (a) Currency Board Arrangements (CBA) and (b) no separate legal tender (dollarization) schemes while the latter (a) crawling bands, (b) within horizontal bands and (c) basket pegs (Mishkin, 1999). It is worth pausing for a moment to recall the definitions of the two stable cryptocurrencies asset classes prior to introducing the traditional exchange rate schemes and commodity standards into cryptocurrencies.

- *Token Stablecoins* wherein only one cryptocurrency in this ecosystem.

[7] We borrow this term from the notion of *price-specie flow mechanism*, attributed to two close friends namely David Hume and Adam Smith and historically ascribed to the context of gold-based coins (coinage) and banknotes.

- *Algorithmic Stablecoins* operates in an extended ecosystem comprising at least two cryptocurrencies which interplay. Usually, such cases include stable assets pegged to an anchor and smart tokens (also called "oracles") with flat supply issued only once which enable anyone to "work-in" the ecosystem as *"central banker"* in making good decisions e.g. setting interest rates, sell walls, feed the system with off-chain prices etc., and in turn receive airdropped rewards.[8]

With the aid of the above definitions we can now concentrate on the commodity standards applied to Stablecoins. Historically, variations of commodity-based regimes have been mostly adopted. In this respect, Diebold et al. (1991) has distinguished five main Standards namely *specie, bullion, exchange, reserve and parity.*

- Under the *Bullion Standard*,[9] the monetary authority is entitled to issue currency as accumulates foreign reserve assets while free and immediate convertibility back to the reserve asset is ensured. This variant of hard peg is related to the Curreny Board Arrangement framework. This type of Stablecoin is backed by the reserves of foreign assets and the originator stands ready to exchange its cryptocurrency on demand for the anchor foreign currency at parity. Hence, the convertibility property applies. Specific identification inventory methods do not apply as in the activities of pawn shops, thus reserves are kept in bulk amounts of collateral assets (usually traditional currencies). It is anticipated that this standard is limited to centralized cryptocurrency schemes.

  As a matter of fact, USD Tether is a working prototype where reserves need to be (at least in theory) fully collaterized for that it is inprobable all depositors to simultaneously request convertibility. Notice that this bears resemblance to electronic banking since lending activity is not assumed. Moreover, the revenue model for the issuer is seignorage from the yield of foreign reserves assets held.

- An *Exchange Standard* system, is a system whereby a certain policy objective is to be achiever, that is to maintain the price of the currency at a fixed parity with the Bullion Standard. In doing so, an intermediary operating mechanism is embedded. Under this mechanism, the currency is not directly convertible to a commodity

[8] A more complex case is Steem Blockchain Dollar (SBD) which is the stable coin of a tripartite ecosystem additionally include an Altchain (Steem) and a smart-token (Steem Power).

[9] This Standard was first adopted in the beginning of the 20th c. It was, however, Ricardo (1816) in his intellectual work with the title *Proposals for an economical and secure currency* who first proposed it almost 100 years earlier. For Ricardo, the standard of value is still gold, though not measured in minted gold coins rather in bullion (gold bars) arguing the full replacement of the former with paper money.

(say gold) like in the Bullion Standard rather indirectly. The currency is pegged to another currency which in turn is convertible to the desired reserve asset. Hence, there is no need to hold any units of the reserve assets. This currency regime fits in the fully collaterized stablecoins case.

By way of example, the Algorithmic stablecoin named "Steem Blockchain Dollar" (SBD) is pegged to the US dollar at parity (1:1) while it is immediately convertible to the Algorithmic (Altchain) cryptocurrency "STEEM" which plays the role of the scarce commodity (like "gold") that independently floats. This means that at any point in time, SBD are convertible to x units of STEEM which correspond to one unit of dollar.

- Under the *Reserve Standard*, monetary mechanisms play the role of stabilization. These are soft-peg standards operating under *crawling bands* for that the price is targeted to be stable within an accepted range. Two cases are DAI and Basis Stablecoins. Both are overcollaterazied (at least 1,5 times).

  In practice, these cryptocurrencies are convertible back to the pledged asset in a scheme similar to Collaterized Debt Positions (CDPs) in derivatives. Credit risk is confined in each bilateral debt position (pledged on-chain asset and issuance of Stablcoin) without spillover liquidation effects.

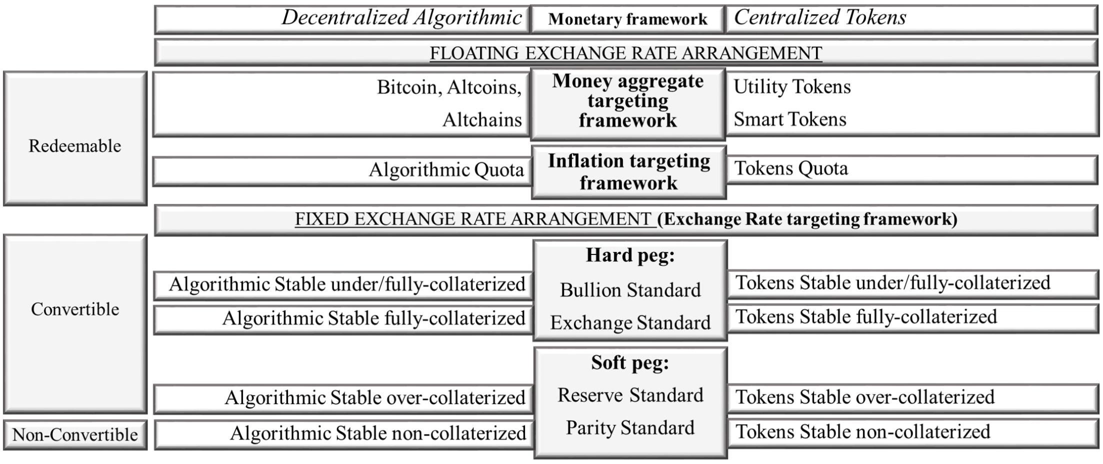
- The *Parity Standard* preconditions no reserves and convertibility is not ensured. The asset is pegged to another asset (again the US dollar or the euro) and uses stabilization mechanisms to target the exchange rate by influencing demand. A working cryptocurrency prototype is Nubits Stablecoin.

It is observed that most cryptocurrencies use as their anchor the US dollar which stands for the Reserve Currency across many Stablecoin ecosystems.

### 3.4.3 The taxonomy of cryptocurrencies revisited

We have employed, so far, money and banking concepts to confer with the varieties of cryptocurrencies. Under this frame, we can revisit the taxonomy of cryptocurrencies. Our previous definitions and classifications were not a matter of mere terminological gymnastics. The analysis points to a rethinking of the monetary nature of each class of cryptocurrencies and its potential to integrate with the financial system. Future theoretical and empirical analyses in this field should demonstrate the utility of the next figure which summarizes this approach.

Exhibit 3.3: Taxonomy of cryptocurrencies revisited




The next section collects findings from the previous conceptual inquiry and attempts to discuss some theoretical issues relevant to future research

## 3.5 Discussion

If the previous inquiry provided sufficient conditions to accept cryptocurrencies' role in the money markets, then the monetary analysis can be broaden. Hence, more technical questions arise. First, how do money supply and demand for such money balances functions look like. More importantly, how many trajectories for equilibrium exist? Second, what is the underpinning theoretical background to include cryptocurrencies, bank (credit) money and rest of markets?

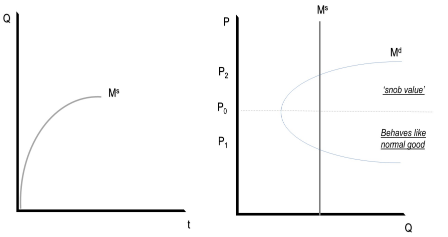
### 3.5.1 Trajectories for partial equilibrium in cryptocurrencies

The taxonomy of cryptocurrencies is partitioned into six supply and demand cases. The figures on the left show the money supply across time. The figures on the right illustrate the interaction between money supply and demand for crypto-money balances.

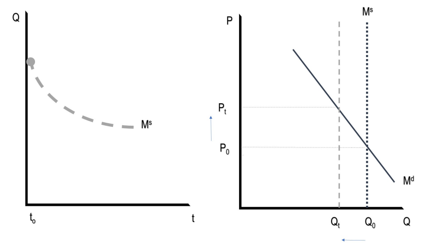
The above leads us to further analyze the supply construction in relation to traditional monetary theories.

[A] **Bitcoin, Altcoins, Altchains** supply is pre-determined following a specific schedule which is non-decreasing (the first derivative with respect to time is non-negative) and increases at a non-increasing growth rate (the second derivative

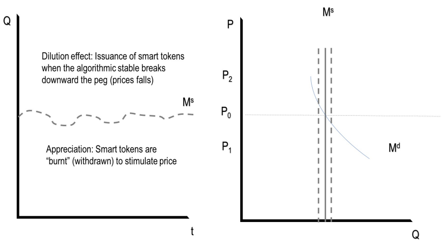
Exhibit 3.4: Plots of cryptocurrencies' demand and supply equilibrium



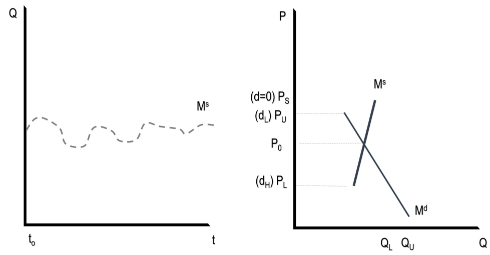
(a) Bitcoin, Altcoins, Altchains



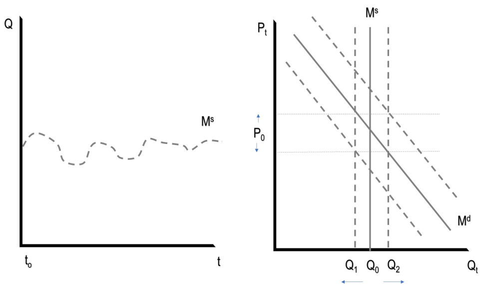
(b) Utility Tokens, Smart Tokens-Stacks



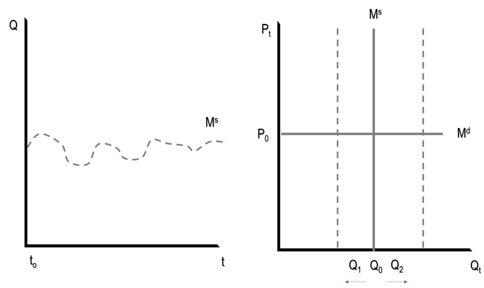
(c) Smart Tokens-Stable



(d) Algorithmic and Token Quota



(e) Stable Algorithmic



(f) Stable Tokens

with respect to time is non-positive) until eventually turns to zero. This process ensures scarcity and exhibits the properties of a concave function. As a result, the supply curve is perfectly inelastic to the level of price. Notice in the next figure that demand for such type of cryptocurrencies seem to exhibit the properties of *Veblen effects*.[10] There is a threshold above which increase in price is accompanied by increase in quantity demanded as consumers demand the good for its status and exclusivity. Under these circumstances, the slope of the demand function turns positive. However, under this so-called *snob value* (Leibenstein, 1950) such cryptocurrencies start off with a normal demand curve that slopes downward from

[10] Veblen goods proposed by Thorstein Veblen. See, *The Theory of the Leisure Class* (1899).

left to right. Monetary theories of bullionism are present in such cryptocurrencies. In Altchains, supply is similar to Bitcoin and Altcoins only that Veblen effects are probable but hoarding is less likely to occur. Altchains allow the development of decentralized applications and can be related to oil and gas commodities for that they are needed to fuel the operation of decentralized applications (dApps). As a result, they have a sufficiently defined demand function compared to Altcoins and Bitcoin.

[B] **Utility Tokens and Smart Tokens-Stacks** are cryptocurrencies in which quantity is implicitly or explicitly controlled. Utility Tokens interact with the real economy for that settle invoices. Smart Token-Stacks are the only media of exchange in a decentralized application connecting users. Thus, there is no firm which receives revenue. Supply is vertical at the launch of these Tokens. The supply could, however, not remain idle for that a large volume of the quantity is retained or will be returned to the issuer of this token. As these token endeavor to appreciate in value, the issuer may program (the case of the Smart Token named Ripple) or decide at discretion (the case of the Utility Token named BinanceCoin) to periodically "burn" (send tokens to wallets with no private keys where remain for ever), thus intentionally reduce supply, in a strategy similar to "treasury stock" in equities. Supply curve with extended dashes depicts this possibility of shifting to the left.

[C] **Smart-Tokens Stable** Stable Tokens-smart which act as governors of Stablecoins are prone to dilution effects in the event of downward destabilization of the Stablecoin price (thus, fall below unity). In such circumstances, new Smart Tokens-Stable are "printed" (issued) in an attempt to build buy walls for buying back the Stablecoin. Hence, by lowering its supply the goal is to increase its price back to unity. In that event, holders of Smart contracts loose value.

[D] **Cryptocurrencies-Quota** aim at reflecting constant purchasing power as are related to a real good or a bundle of real goods. In Tokens-Quota, the issuer controls how supply expands (by selling Tokens) and contracts (by redeeming Tokens). Tokens face demand and supply curves (lines) that have a kink at a level of price and quantity respectively. In a given good market, the seller will reach a quantity that turns inelastic to price changes for that he has no incentive to produce the underlying asset as profit turns negative.

[E] **Algorithmic-Stable** aim at retaining fixed exchange rate relative to another anchor (usually sovereign currency such as the US dollar). As a result, supply varies on the basis of stabilization mechanisms. Notice that demand has its ordinal shape for that some of these Stablecoins are accompanied with decentralized services. By way of example, over-collaterized (e.g. DAI) allow for short-term leverage that comes with a cost (loan interest rate upon redemption). Demand for money balances is negatively affected the higher this rate is.

[F] **Token-Stable** hold off-chain (not on the blockchain) reserves. Usually traditional (sovereign) currency (US dollar, the Euro) and commodities (gold etc.). Hence, supply varies but as the issuer operates as a bank supply is more likely to constantly expand. Notice than demand is less steep than in the case of Algorithmic Stable. Actually, it is flat for that the centralized entity always stands ready to convert its cryptocurrency on demand.

The fundamental monetary identity states that the amount of currency issued $C^e$ is the difference between total assets (A) and total liabilities (L) in central bank's statement of financial position (balance sheet). This can be broadly defined as follows

$$C_t^e = \Sigma A_t - \Sigma L_t = \theta_t - K_t$$

where $\theta_t$ include the net position (difference between claims and liabilities) in foreign assets (could be US dollars, gold or even other on-chain asset) and of course domestic assets. In the conventional banking system, $K_t$ stands for deposits (reserves) of commercial banks allowed to create *inside money* held at the central bank. The summation of the latter and currency issued equals the monetary base (B).

The balance sheet identity is more evident in convertible Stablecoins, where $\theta_t$ is positive for that is backed by reserves. This is not the case for non-convertible Stablecoins earlier analyzed since they lack collateral. The asset-side of Algorithmic coins like Bitcoin broadens as their own digital durable commodity accumulates. Contrary, Tokens are private fiat monies for that their asset-side constitutes of deferred assets, thus the production (acquisition) of economic assets expected to be consumed in a later day. This issued money can claim amounts of this asset by settling the payment, thus by redemption.

In traditional currencies we know that currency can be either held by the general public in the form of coins and banknotes ($C$) or deposited in a commercial bank ($C^b$) for safety and for accessing the electronic system of accounts. The summation of $K_t$ and

$C^b$ are commonly referred to as commercial bank's liquid assets. All together, we derive:

$$B_t = C_t^e + K_t = C_t + C_t^b + K_t = C_t + R_t$$

Also, recall that *inside money* or "secondary money" is created by the issuance of deposits (D) regulated by the central bank which controls liquid requirements (R) denominated in the same unit of account and resulting to the increase of the money supply (M) as follows.

$$M_t = C_t + D_t(R)$$

But it is self-evident, that the absence of portfolio management activities (D=0) and bank reserves (K) as well as the coincide of currency held by the public (cash at hand) with currency held in banks vaults ($C^b$) results to a different identify compared to the conventional one. In cryptocurrencies, it can be said that base money (or narrow money) equals money supply which equals to currency issued. More formally,

$$B_t = M_t - D_t + R_t = C_t - C^b + R_t = M_t = C_t^e$$

### 3.5.2 Cryptocurrencies in a general equilibrium framework

Moving from the partial equilibrium analysis to a more general context, we can associate cryptocurrencies as money balances with the rest of the economy. We align with the literature about the inappropriateness of "decontaminated physical environments of typical Arrow-Debreu environments" in studying cryptocurrencies (Verme & Benavides, 2013). In doing so, we show an introductory theoretical framework akin to the model of Freixas & Rochet (2008) in their own initial examination of the banking sector. We extend by introducing the two fundamental categories of cryptocurrencies namely Algorithmic issued in a pre-determined fashion via a blockchain and centralized Tokens issued by private firms. We skip for now Stablecoins pegged to the economy's functional currency for that have litter to offer to the discussion.

For simplicity, we assume as in Freixas & Rochet (2008) an environment with complete markets, lack of uncertainty and a two-dates model (t= 1,2).[11] We have the next representative types of agents in the economy: firm, household, (commercial) bank and blockchain (distributed ledger). We skip the case of currency balances (coins and banknotes) which pay no interest. Household owns banks and firms. This is a closed economy with a single physical good produced taken as the numéraire which is to be

[11]Similar results should be derived under the assumption of infinitely lived households.

consumed between the two dates in accordance with household's inter-temporal decision. The household faces a consumption decision between two dates and an allocation of savings decision between

[A] bank deposits (D) which offer return: $r_d$. For future research, we could separate (a) bank deposits between checking and current accounts which are convertible to "outside money", thus currency issued by the central bank and are no-interest bearing digital assets from (b) time deposits that offer an interest rate, indeed. For simplicity we could think of one type of deposits.

[B] bonds (B) issued by firms and banks pay the nominal interest rate $r_f$ and $r_b$ respectively

[C] loans (L) issued by banks as part of their portfolio management activities which pay nominal interest rate: $r_l$

[D] we introduce cryptocurrencies (CC) which offer return denoted as $r_{cc}^j$. The superscript j denotes the cryptocurrency asset classes i.e Algorithmic cryptocurrencies denoted as $r_{cc}^A$ and Token cryptocurrencies issued by the productive sector (firms) denoted as $r_{cc}^T$ for that can be backed by goods. As mentioned, we skip the case of Stablecoins which pay no nominal return, but we do discuss some relevant perspectives throughout this analysis.

Loans are provided by licensed banks which can issue deposits and create claims against the borrower. In this perfect economy, securities (debt and equities) and bank deposits are perfect substitutes (Freixas & Rochet, 2008). This result is extended to cryptocurrency assets. We also add the assumption that there is no credit market for cryptocurrencies, only spot. So, loans can only be granted in the functional unit of account. Each balance sheet would be as follows:

Exhibit 3.5: Assets and Liabilities by agent

| Agent | Assets | Liabilities and net worth |
|---|---|---|
| Household | Bonds, Deposits, cryptocurrencies (Algorithmic and Tokens) | Initial endowment, consumption |
| Firms | Investments | Bonds, Loans, **Token Cryptocurrencies** |
| Banks | Loans | Bonds, Deposits |
| Blockchain | Distributed Ledgers assets | **Algorithmic cryptocurrencies** |

**The Household**

The household maximizes the underlying utility function (U) by making the consumption decision $C_1, C_2$ and the allocation of savings decision $B_h, D_h, CC_h^j$ with respect to the balance sheet constraints. For the Household, $\mathcal{P}_h$

$$\begin{cases} maxU(C_1, C_2) \\ B_h + D_h + q_1^j CC_h^j = \phi_1 - C_1 \\ pC_2 = \Pi_f + \Pi_b + (1+r)B_h + (1+r_d)D_h + q_2^j CC_h^j + DLA_h \end{cases}$$

The term p denotes the price of consumption in period 2. The term q is the exchange rate between the functional unit of account and the underlying cryptocurrency j. In effect, the proportional change of the exchange rate between the two periods can be viewed as a return, thus ($\frac{q_2^j}{q_1^j} = r_{cc}^j$). DLA is the increase in Algorithmic coins given to households through a subsidy. In the literature, this is how these class of cryptocurrencies such as Bitcoin are modeled (Garratt & Wallace, 2018) while mining cost usually enters in the utility function with a negative sign as disutility. We extend to show that this is not the case with Tokens which arrive as alternative credit line used to finance investments. Later, these would be further explained under the firm and blockchain agents' sections.

The balance sheet constraint is given by the last two equations above. The second equation states the allocation problem on the left while on the right shows the amount of savings (S) as the difference between an arbitrary parameter for an initial endowment (of the consumption good used as the numéraire) denoted by $\phi_1$ and the selected consumption in period 1 (Freixas & Rochet, 2008). Since currency (coins and banknotes) issued by the Central Bank and Stable cryptocurrencies pay no interest and the latter do not appreciate in value, there is no coherent reasoning to include the latter to the balance sheet (or budget) constraint. In the macro-monetary literature, there are models addressing the issue of introducing money balances to this problem. Sidrauski (1967) indirectly enters this in the utility function while Lucas (1980) as cash advances sufficient to cover next period's needs. These comments could be useful for future research in building theoretical models with all varieties of cryptocurrencies.

Going back to the above utility maximization problem, according to Freixas & Rochet (2008) this has an interior solution only when interest rates are equal. Moreover, we extend to include cryptocurrencies' yield. The Lagrangian function for the above setup is as follows:

$$\mathcal{L} = U(C_1, C_2) + \lambda(\phi_1 - C_1 - B_h - D_h - q_1^j CC_h^j) \\ + \mu(\Pi_f + \Pi_b + (1+r)B_h + (1+r_d)D_h + q_2^j CC_h^j + DLA_h - pC_2)$$

And, the FOCs result to:

$$\frac{\lambda}{\mu} = (1+r) = (1+r_d) = \frac{q_2^j}{q_1^j} = (1+r_{cc}^j)$$

While the solution for the inter-temporal consumption decision is as follows:

$$\frac{u\prime_{c1}(C1, C2)}{u\prime_{c2}(C1, C2)} = \frac{\lambda}{\mu p}$$

And, the last term is equal to the interest rates adjusted for the price level p. Hence, $r = r_d = r_{cc}^j$. Notice that for households, bond $B_h$ holdings are the summation of firm's bonds and bank's bonds.

The last return refers to holdings of cryptocurrencies either Algorithmic or Tokens. While for the former the return is only in the form of price appreciation as it independently floats against the functional currency, Tokens at issuance may promise an nominal rate of return determined by the originator when exercised for payments. So, this higher purchasing power may be ex-ante determined resulting to a fixed exchange rate arrangement with no price appreciation as the return arrives in the form of a spread between this Token and the functional currency.

**The Firm**

The firm drives the economy for that chooses the level of investment. To do so, the firm faces the classic (internal and external) financing decision problem (Myers & Majluf, 1984). Interestingly, we embed the alternative option of issuing centralized Token (IOU) cryptocurrencies denoted as $CC^T$ (or CCT) The term $q^{CCT}$ shows the exchange rate between the Token and the functional unit of account. This adjustment is required for that all other assets are directly expressed in the functional unit of account. More analytically, for the Firm, $\mathcal{P}_f$

$$\begin{cases} max\Pi_f \\ \Pi_f = pf(I) - (1+r)B_f - (1+r_l)L_f - q_2^{CCT} CCT_f \\ I = B_f + L_f + q_1^{CCT} CCT_f \end{cases}$$

The last term on the right in each equation represents the cost of issuing Token cryptocurrencies net of transaction costs (possibly a discount offered to consumers) and the amount of cryptocurrency raised to finance the investemnt decision respectively. $f$ is the production function. Assuming that there is no depreciation, maximization of the profit function with respect to the financing constraint implies that $pf\prime(I)$ equals to $(1+r)$ which also equals to $(1+r_l)$ as well as to $\frac{q_2^{CCT}}{q_1^{CCT}} = r_{CCT}$. Again, in this perfect environment, the trivial interior solution is: $r = r_l = r_{CCT}$

**The (commercial) Bank**

Commercial banks create "inside money", thus the supply of amount L, attracts deposits D against which offers an interest rate and issues bonds B for financing its operations. For the Bank, $\mathcal{P}_b$

$$\begin{cases} max\Pi_b \\ \Pi_b = r_l L_b - rB_b - r_d D_b \\ L_b = B_b + D_b \end{cases}$$

Solution does not differ. Hence, $r = r_l = r_d$

**The Blockchain (Distributed Ledger Assets)**

This is the case for Algorithmic cryptocurrencies denoted as $CC^A$ (or simply CCA) like Bitcoin expressed in units of the good which plays the role of the functional unit of account in this economy. For simplicity, drop any considerations for the case that households act as miners and therefore incur (sunk and operating) costs in competing for new coins. In the literature, agents' behavior in such peer-to-peer monetary environments is thoroughly examined in Schilling & Uhlig (2019). The blockchain is a public infrastructure. It is not a household or a private firm. Thus, there is no utility or profit maximization function underpinning the supply side.

For the blockchain, two factors are important. First, the schedule of the supply path in accordance to a fixed and non-negative parameter denoted as k. The way blockchain assets enter into a macro-monetary framework not need to be far away from the concept of a direct subsidy to households. Since, blockchain assets are not financial instruments which simultaneously create a liability like bonds and Tokens, then we can assume that the newly emitted units $CCA_{t+1} - CCA_t = \Delta CCA_t$ are given to households as helicopter drop.[12]

In the household maximization problem, this is denoted as DLA (distributed ledger assets). Second factor of importance is the money price of the Algorithmic coin, that is the exchange rate expressed in the functional currency (q). Or, put it differently,

[12] An expression historically attributed to Milton Friedman.

this is the fraction of the two price levels if the cryptocurrency is looked at as media of exchange. As mentioned above, the rate of return of the Algorithmic coin measured in terms of the functional currency is denoted as $r_{CCA}$. Therefore,

$$\begin{cases} CCA_{t+1} = \Delta CCA_t + CCA_t = CCA_t(1+k) \\ \dfrac{q_2}{q_1} = r_{CCA} \end{cases}$$

If the exchange rates moves up, the purchasing power of the Algorithmic cryptocurrency increases when converted back to economy's functional unit of account (the good) and vice versa. From the asset-side, their creation resembles that of durable goods (commodities) which accumulates and do not suffer from depletion.

**Equilibrium**

As said, it arrives as a typical conclusion that in such Arrow-Debreu environments traditional money that pays no interest is not attractive. Hence, households only hold bonds and deposits and possibly cryptocurrencies able to yield a return, yet all returns are equal. Banks earn zero profit and the solution shares common characteristics with Hagen (1976) and E. F. Fama (1980) interpretation of the Modigliani-Miller theorem in financing policy and banking policy respectively. The extended solution compared with Freixas & Rochet (2008) is derived as follows:

- a vector of rate of returns given by $(r, r_l, r_d, r_{cc}^j)$
- a vector of the household's balance sheet $(C_1, C_2, B_h, D_h, CC_h^j)$
- a vector of the firm's balance sheet $(I, B_f, L_f, CCT_f)$
- a vector of the bank's balance sheet $(L_b, B_b, D_b)$

In addition, a vector of the blockchain balance sheet (CCA) given above. Agents optimize respective behaviors: $\Pi_f$, $\Pi_h$, $\Pi_b$ while the blockchain follows its own exogenous path. At equilibrium, markets clear and the next conditions should hold as in Freixas & Rochet (2008) while we include cryptocurrency holdings.

The good market as Investment equals Savings: I + DL assets = S

The bank deposits market: $D_b = D_h$

The "inside money" market: $L_f = L_b$

The capital market: $B_h = B_f + B_b$

The "cryptocurrency" market: $CC_{DL}^A + CCT_f^T = CC_h^j$

And the only possible equilibrium is such that $r_l = r = r_d = r_{cc}^j$. The solution of identical returns to traditional securities, bank loans and alternative assets (either Algorithmic or

Token cryptocurrencies) while money balances in traditional cash (and possible Stable cryptocurrencies) are absent is far from appealing. The above model aimed at showing a general framework underpinning the main varieties of cryptocurrencies in modeling issuance and circulation. A further discussion with regards to the monetary functions of cryptocurrencies better served in the financial system is offered by the next section.

### 3.5.3 Money and banking competition the way forward

The above trajectories partial equilibrium is more than schematic. We can now envisage how competition with traditional banking in the money markets is likely to occur. First, (a) Token cryptocurrencies under quantity rules by meeting the deferred payments function can introduce competition to commercial banking's checking accounts and pledged asset (short-term) lines of credit. Second, (b) Stable cryptocurrencies by meeting the media of exchange function can introduce competition to commercial banking's deposits similar to e-money issuance institutions while operating in tandem with the economy's functional currency. Third, (c) Algorithmic cryptocurrencies under quantity rules such as Bitcoin pertain investment nature (storing value) whose intrinsic value stems from the usage of these coins in the decentralized built-in blockchain. More broadly speaking, it would be expected to compete with securities and commodities in fulfilling the store of value and investment motives. Notably, traditional currencies are still of the greatest value and importance to the real economy and surprisingly to cryptocurrency ecosystems as well for that they convey the intelligence of the prevailing numéraire.

As a result, commercial banking may face fierce competition in fully-collaterized (convertible) checking accounts and over-collaterized banking products such as factoring and cheque pledging, but not in lending activities. On the other hand, outside money competition with central banking may result in circulation of private fiat-currency in tandem with cryptocurrencies. Hence, all cryptocurrencies are aiming to convey adding value. It is open to debate (and empirical investigation) that the supply side of each cryptocurrency asset class abides by traditional monetarist theories as follows.

- Algorithmic cryptocurrencies following quantity rules: Monetary theories of bullionism mimicking precious metals are present and the issue of price instability has been considerably raised in the literature (Senner & Sornette, 2019). As demand increases due to speculation and supply is constrained to follow its pre-known growth path, prices inevitably soar.

- Token cryptocurrencies following quantity rules: Quota cryptocurrencies, thus under the price-specie standard which we earlier defined freely float, yet a good or a bundle of good or even a basket of currencies could be the underlying assets. The significance of liquidity premiums might be useful in these Token economies where money supply is implicitly exogenous analogous to the liquidity preference theory. In the same spirit, modern theories of endogenous money may be related to Asset-backed (with real goods) Tokens issued by productive firms when in need for funds. Recall the *Real-bills doctrine* which postulates the direct link of vendors' products to money supply (G. A. Selgin, 1988). These Tokens may yield a rate of return (as the issuer offers a discount for settling payments compared to the economy's functional currency). In this context, firms make the banking sector redundant for working capital needs and use their assets as collateral. This could be a private pledged credit line readily settle payments for goods. This means that firm will become issuers of their media of exchange. This is not new. Birch & McEvoy (1997) credit to Edward de Bono the pioneer idea of private currency as a financial claim on sold products or services by the issuer. According to the authors the latter portrays a transaction where IBM issues "IBM dollars" which consumers use to purchase IBM products or services. In this self-regulated system where each firm can cost-free enter into the money-issuing market, exchange rates operate as the decentralized clearing house in the market

- Stable cryptocurrencies: The theory of Quantity Theory of Money is found in much substances of stable applications as primary concern is given to adjustments to the aggregate level of supply so as to meet a predetermined objective, usually peg the exchange rate to an anchor. As a matter of fact some non-collaterized Stablecoins use the fundamental identity as the mechanism for achieving price stability. This means that quantity is adjusted in response to changes in price.

## 3.6 Concluding remarks

In this paper we examine how cryptocurrencies straddle the margins between the definitions of currency, system of accounts and outside money, the hybrid of hybrid being able to take all complementary properties and consolidate them. In that event, their advent as alternative (peer-to-peer) exchange systems which sufficiently meet the functions of store of value, media of exchange and deferred payments, in turn, at least outwardly challenges and as though may supplant the established today's International Finance paradigm for that can transcend banking in an imperative way.

# Chapter 4

# Are Stable cryptocurrencies exempted from Impossible Trinity?

This paper provides an empirical framework analogous to Impossible Trinity for exploring monetary arrangements across Stablecoins wherein reserves are held. While the hypothesis is supported for all cryptocurrencies in question, the trade-off combination among exchange rate stability, capital openness and monetary independence varies with the categorical types of Stablecoins. This uncovers the inherent constraints of their monetary structures compared to the rest genres of cryptocurrencies.

## 4.1 Introduction

Ever since the launch of Bitcoin and its offspring, examination of cryptocurrencies' trading activity from the empirical finance viewpoint has received much attention, and continue to do so in examining price discovery and spillover effects (Cahill et al., 2020), market efficiency (Gandal et al., 2018) and portfolio diversification and hedging (Corbet et al., 2018). The particular monetary arrangements found in Stable cryptocurrencies (colloquially referred to as Stablecoins), however, have not been properly (a) classified and (b) studied within an empirical international finance and banking context. Our findings of existence of the degree of achievement along the three dimensions of the Impossible Trinity hypothesis namely monetary independence, exchange rate stability, and financial openness for a representative sample able to cover all varieties of Stablecoins provide fresh empirical insights and arguments to this growing literature with respect to the success of their embedded exchange rate stabilization mechanisms.

While monetary autonomy is self-explanatory for cryptocurrencies like Bitcoin with pre-determined supply path, it is of great interest to probe into the monetary structures of Stablecoins. In these supply contracts and expands and capital restrictions apply due to the existence of reserves as the exchange rate arrangement adheres to a price rule. If Stable cryptocurrencies, therefore, claim the role of global monetary assets freed from sovereign limits and national boundaries, it is critical to explore whether they adhere to traditional monetary frameworks.

## 4.2 Related literature

Interest in the monetary perspectives of cryptocurrencies recently started to grow (Bolt & Van Oordt, 2016), especially following the advent of a new breed of cryptocurrencies also known as Stablecoins wherein their price is thus pegged to an anchor, usually the US dollar at parity. For Senner & Sornette (2019), cryptocurrencies are built on outdated monetarist theories which inevitably result to price instability. Corresponding to this, Stablecoins were developed aiming to address the issue of excessive price variation in cryptocurrencies like Bitcoin (Caginalp, 2018). In the literature there are similar works which explore the monetary aspects of cryptocurrencies in general (Moin et al., 2019; Nakavachara et al., 2019) and their price stabilization mechanisms in particular (Mita et al., 2019; Calcaterra et al., 2019; Pernice et al., 2019). The latter extracts useful general concepts by reviewing and comparing 24 Stablecoin projects. But in these studies the methodological approach employed is limited to conceptual and theoretical investigations. In this paper we provide a conceptual framework for the analysis of the exchange rate mechanisms conditional on Stablecoin asset-classes accompanied with an empirical study from the monetary viewpoint. This is the first work in this attempt.

The empirical framework empoyed is analogous to the traditional theory of international monetary economics referred to as Impossible Trinity (known as the *Mundell-Fleming trilemma*) developed independently by Fleming (1962) and Mundell (1963). The traditional hypothesis postulates that only two out of three major monetary objectives namely money supply independence (monetary autonomy), financial integration (capital mobility) and exchange rate stability are simultaneously met. Many empirical studies have extensively examined traditional currencies (Rose, 1996; Bluedorn & Bowdler, 2010) while long-lasting debate in the literature remains the construction of appropriate proxy indexes to measure the three underlying monetary concepts. More recently, Canale et al. (2018) examine the trade-off in the post-crisis Eurozone while Aizenman et al. (2013) emphasize the complexity of modern financial globalization to proposes the modification into *Policy Quadtrilemma* for addressing this parameter of increasing importance.

While cryptocurrencies correspond to global assets not linked to national economies, it is noted that the theoretical notion of global currencies within an international setting is not new in the monetary theory literature (Obstfeld & Rogoff, 2002). Moreover, our study can be viewed as complementary to the theoretical inquiry of Benigno et al. (2019) who establish a model featuring two national currencies and one cryptocurrency to conclude that the latter when backed by reserves adds restrictions to the classic Impossible Trinity.

## 4.3 Decoding monetary intervention in Stablecoins

Using four representative Stablecoins (in parenthesis the trading ticker) namely DAI (DAI), Steem Blockchain Dollar (SBD), USDTether (USDT) and TrueUSD (TUSD), we focus on their monetary arrangements. The selection is not arbitrary for that these correspond to the four general categories of Stablecoins which we illustrate succinctly.

I **Under/fully-collaterized Stable Tokens** are pegged and are convertible to traditional currencies against which they hold reserves. This is the case of USDTether, and TrueUSD. In theory, they are fully collateralized for that the originator (a limited company) commits to peg the Stablecoin to a foreign anchor (usually the US dollar) on demand. Unlike the other Stablecoins, there is "prohibition" against holding domestic cryptocurrencies or engaging in open market operations. Under this frame, the monetary base is beyond the control of the originator. It increases when users sell US dollars for the Stablecoin at the fixed exchange rate (at parity) and decreases when the reverse transaction takes place. The term "under/fully collaterized" refers to the uncertainty that there are always enough deposits (in US dollars) so as to meet withdrawals in full (a concept similar to bank runs). This is can only be periodically verified following audits of the company's financial statements.

II **Over-collaterized Stable Algorithmic** are pegged, yet are non-convertible, to traditional currencies. This is the case of DAI which operates in tandem with another cryptocurrency called MakerDAO. The latter is a Smart Token which independently floats with fixed supply responsible to monitor Stablecoin's price stability and act if required. In over-collaterized Algorithmic Stablecoins, reserves in domestic (DAI and MakerDAO) and foreign (in other cryptocurrencies) assets are held.

III **Fully-collaterized Stable Algorithmic** hold domestic reserves but not foreign reserves. This means that the Stablecoin can be converted to another cryptocurrency belonging to the same ecosystem. This is the case of Steem Blockchain Dollar whereas STEEM is the other cryptocurrency which independently floats. Note that this not a Smart Token cryptocurrency but an Altchain cryptocurrency. Altchains are alternative to the Bitcoin Blockchain and their supply schedule is similar to Bitcoin's. The most popular case of Altchains is the Ethereum platform whereby users develop smart contract on their own. STEEM is an algorithmic coin whereby users contribute content to STEEM blockchain-based applications. In turn, they get paid in domestic assets such as SBD (there is also another non-tradeable called Steem Power) backed both by the STEEM algorithmic whose pre-determined supply path renders it a scarce digital commodity.

IV **Non-collaterized Stable Algorithmic**, so far, are the most difficult decentralized projects to implement. In this work, we do not empirically test non-collaterized Stablecoins for that most cases are short lived. But, we do present their specific monetary tools for achieving exchange rate stabilization. A controversial case was Basis.[1] Also, worth mentioning is the Algorithmic Stablecoin referred to as Nubits which circulates with a Smart Token referred to as NuShares. This is another unsuccessful case for that the peg has broken quite a lot of times. Closely, a very recent development is a Stablecoin called Ampleforth. The creators claim that they have devised outside money in the form of synthetic commodity which has absolute scarcity but lacks non-monetary use value. The main point is that the algorithm does not contract and expand the future supply rather all circulating supply in targeting price stability. Put it differently, holders observe reduction or increase (in units of currency) in their wallets as the protocol reacts to price-information while users are not diluted. This was issued in late 2019 and data are still limited in size.

[1] In the Basis ecosystem two more cryptocurrencies were supposed to exist namely BasisShares and BasisBonds. In the United States, the Stock Exchange Committee (SEC) openly regarded these cryptocurrencies as "securities" imposing compliance with relevant legislation. As a result, Basis cryptocurrency had to terminate operation in late 2018 and return funds to investors.

To recapitulate, Stable Tokens are centralized (IOU) cryptocurrencies. The originators of Stable Tokens are limited liability companies which receive off-chain assets (thus, not cryptocurrencies issued on-chain via blockchains). This can be analogous to e-wallets issued by electronic bank institutions allowing the depositor to transfer and withdraw funds. The difference is that access to funds rests with the depositor. Stable Tokens do not act as custodian of the funds, unless the depositor wants to. For that reason they are closer to cash at hand rather cash equivalents (typical bank deposits). This applies to all cryptocurrencies. The most successful case of Stablecoins is USDTether for that it ranks first among cryptocurrencies in terms of daily volume, thus even higher than the market leader Bitcoin. In effect, the USDT/Bitcoin pair has outrun the US dollar/Bitcoin pair as the most traded pair in digital exchanges marking the strong position and high demand for Stablecoins. Other recent Stable Token initiatives include Paxos, USDCoin and BinanceUSD.

Contrary, Stable Algorithmic are decentralized cryptocurrencies issued on-chain (thus, automatically on the blockchain via smart-contracts). As exemplified above all these ecosystems come with at least two cryptocurrencies. Increase in demand for Smart Tokens acting as oversight-governors is tied up in a critical manner the success of its respective Stablecoin. In these ecosystems, Smart Tokens' essential role is that of means of payment (for settling fees). When price destabilization in Stablecoins is persistent, Smart Tokens may suffer from dilution and devaluation. In contrast, the more successful the Stablecoin the higher the demand for the Smart Token (and price since their supply is non time-varying). In this spirit, collateral assets used in Stablecoins consist of three types of reserves as follows.

- **Self-collateral** which we refer to as domestic reserves and include either (a) cryptocurrencies of the same ecosystem (such as STEEM coins in the SBD stablecoin case or MakerDAO coin in the DAI stablecoin case) or (b) the stablecoin itself. The latter refers to the right granted to the algorithm to create (print) Stablecoins out of thin air. This is somewhat analogous to deposit (debits) this new money into commercial banks' checking accounts with the central bank when a security is bought.

- **On-chain collateral** are cryptocurrencies not belonging to the same ecosystem as above. By way of example the DAI stablecoin primarily accepts Ethereum as collateral. On-chain collateral is the only way to establish decentralized peer-topeer applications, thus without a third-party acting as custodian in diminishing counterparty risk. Smart-contracts can only communicate with cryptocurrencies (being distinguished by alphanumeric characters).

- **Off-chain collateral** are traditional currencies (in euro, US dollar etc.) and commodities (gold etc.). A third party accepts deposits. Then, the issuer manually executes the transaction on the blockchain to deposit x amount of Stablecoins to a specific wallet requested by the depositor at the pre-arranged exchange rate.

All said, the next table delivers a visualization of the structure of the balance sheet for each case of Stablecoin.

Exhibit 4.1: Visualization of Stablecoins' balance sheets

| Stablecoin | Assets (Reserves) | Liabilities (Currency) |
|---|---|---|
| Under/Fully collaterized | [1] Foreign reserves in off-chain assets such as currencies (US dollar, euro) and commodities (Gold) | Token Stable cryptocurrencies |
| Fully collaterized | [1] Domestic reserves in on-chain cryptocurrencies (the Stable itself), [2] Domestic reserves in other (internal) on-chain cryptocurrencies belonging to the same ecosystem (usually Altchains) | Algorithmic Stable cryptocurrencies |
| Over collaterized | [1] Foreign reserves in external (outside the same ecosystem) on-chain cryptocurrencies pledged, [2] Domestic reserves in on-chain cryptocurrencies (the Stable itself), [3] Domestic reserves in other (internal) on-chain cryptocurrencies belonging to the same ecosystem (Smart Tokens) | Algorithmic Stable cryptocurrencies |
| Non collaterized | [1] Domestic reserves in on-chain cryptocurrencies (the Stable itself) | Algorithmic Stable cryptocurrencies |

Changes in money supply has long been perceived to be the main factor in meeting macroeconomic performance objectives i.e exchange rate price, inflation of supply level. Stablecoins exercise discretionary monetary policy as their supply contracts and expands in an attempt to retain their price stable, thus not their purchasing power. The most interesting monetary instruments for intervention are found in Algorithmic Stablecoins. These can be said that are soft pegs for that they vary within a narrow band while Stable Tokens are hard pegs (Mishkin, 1999).

Historically, central banks engage in open market operations, establish reserves restriction and set reference interest rates. Below, we aim at examining the existence of these tools in Stablecoins. Recall that in cryptocurrency environments there is no commercial banking in the middle. The originator of Stablecoins acting as central banker directly interacts with the users (holders of electronic deposits). The conventional tools used for stabilization purposes in Stable cryptocurrencies are as follows:

- **Open Market Operations:** consist of
  (a) outright (permanent changes in supply) via Domestic and Foreign reserves (similar to Monetary Stabilization Accounts in conventional central banking's practices). An increase, thus sale of assets aim at buying back the currency and stimulate price upwards,
  (b) repurchase agreement (temporary changes in supply) via forward and option-like contracts. These operations are executed as reverse transactions aligned with Monetary Stabilization Bonds practices used by central banks.

- **Standard facilities:** Users (counterparties) can use either lending facilities or/and deposit facilities.
  (a) The first offers liquidity by creating Stablecoins upon pledging an amount of on-chain collateral. The level of interest rate is governed by the Smart Tokens in the ecosystem.
  (b) The second is used to withdraw money supply from the ecosystem (a notion called "parking Stablecoins") and in turn interest rate accrues (paid in Stablecoins) by analogy to short-term savings accounts.

- **Reserve requirements:** Such requirements refer to on-chain collateral requested. As the ratio of the value of the collateral to the value of Stablecoins becomes higher, *ceteris paribus*, demand for Stablecoins lessens and in its aftermath supply.

Interest rates are greatly used in non-collaterized Stablecoins while reserve requirements in over-collaterized Stablecoins. The reserve requirement increases when the exchange rate falls below the target rate as the exchange rate of foreign (on-chain) asset fluctuates according to the price-feeds provided by Smart Token holders (oracles). Margin calls require by depositors the addition of collateral otherwise liquidation mechanisms are triggered. In this case, the foreign asset used as collateral is partly seized (sold via digital exchanges) in exchange for the acquisition of the domestic currency (the Stablecoin) from the market. As a result the latter is permanently withdrawn lowering overall supply. The next table collects the liquidity mechanics embedded for setting buy and sell walls for each case. Not available (n/a) indicate tools that are not used.

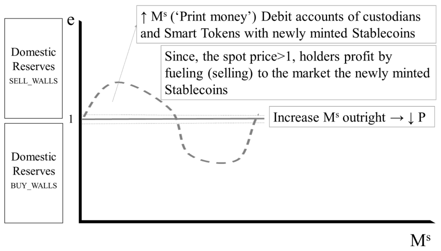
Exhibit 4.2: Monetary tools in Stable cryptocurrencies

| Tool / Stablecoin | Under/fully coll. (USDT, TrueUSD) | Fully coll. (SBD) | Over coll. (DAI) | Non coll. (Nubits) | Non coll. (Basis) |
|---|---|---|---|---|---|
| Tools for setting BUY WALLS when price falls below parity (Reduce exchange rate, expand money supply): | | | | | |
| OMO outright | n/a | n/a | Print Domestic (DAI) to buy Domestic Smart Tokens | Print Domestic (Nubits) | Print Domestic (granted to Smart Tokens) |
| OMO repo | n/a | n/a | n/a | n/a | n/a |
| Lending facility | n/a | n/a | Reduce lending interest rate | n/a | n/a |
| Deposit facility | n/a | Reduce deposit interest rate | n/a | Reduce deposit interest rate | n/a |
| Reserve requirements | 100% (foreign off-chain) | 100% (domestic) | Increase (foreign on-chain) over-collateral | n/a | n/a |
| Tools for setting SELL WALLS when price goes higher than parity (Increase exchange rate, contract money supply): | | | | | |
| OMO outright | n/a | n/a | Sell Foreign reserves (on-chain collateral and Smart Tokens) to buy back the Domestic (DAI) | n/a | n/a |
| OMO repo | n/a | n/a | n/a | n/a | Sell bonds to buy back the Domestic and then reverse |
| Lending facility | n/a | n/a | Increase lending interest rate | n/a | n/a |
| Deposit facility | n/a | Increase deposit interest rate | n/a | Increase deposit interest rate | n/a |
| Reserve requirements | 100% (foreign off-chain) | 100% (domestic) | Reduce (foreign on-chain) over-collateral | n/a | n/a |

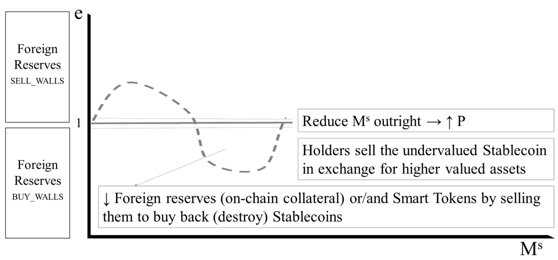
Open Market Operations (OMO) via Smart Tokens (recall the governor-bankers of Stablecoins) are the main means by which normalization of the exchange rate (thus to parity) is achieved and are present in every class of Algorithmic Stablecoins. A graphical analogue of the four main instruments for supplying and withdrawing liquidity namely domestic reserves, foreign reserves, interest rates (lending and savings) and repurchase agreements (convertible bonds) are next exhibited.

At this point, the analogy between the stabilization mechanism in Stablecoins and central banking's monetary instruments is complete. To mention a detail, the monetary objectives in each Stablecoin category are not alike. The next empirical study should make this point more evident.

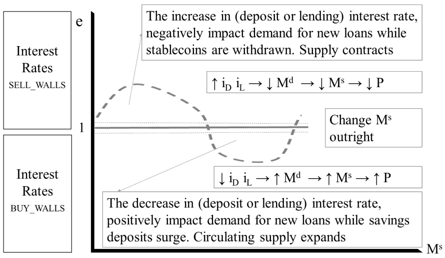
Exhibit 4.3: Monetary stabilization mechanisms in Algorithmic Stablecoins



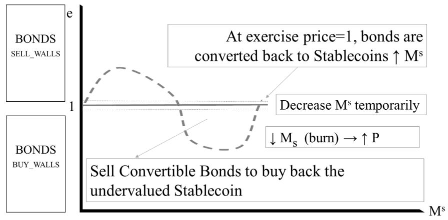

(a) via Domestic (on-chain) Reserves




(b) via Foreign (on-chain) Reserves




(c) via interest rates




(d) via repurchase agreements

## 4.4 Preliminaries

Empirical research studies on the Impossible Trinity involve the construction of indicators. To address the issue of proxies, we use the methodology of Aizenman et al. (2013) as benchmark. All three indexes fall between 0 (lowest) and 1 (highest).

First, the index for the degree of monetary independence (MI) would be:

$$MI_t = 1 - \frac{corr(i_t, M_t) - (-1)}{1 - (-1)}$$

In the literature, correlation between interest rates of a home and base country with which the former has strong connection is usually examined. But, interest rates are absent in cryptocurrencies for that they lack, so far, *inside money*. To deal with this, we choose as proxy the correlation between the daily rate of return of Bitcoin and the change in each Stablecoin money supply during the last three days. The logic behind this is simple. Bitcoin dominates the cryptocurrency markets and, therefore, is strongly affiliated with all other cryptocurrency ecosystems. Positive correlation signals low monetary independence. The rise of opportunity cost (the nominal yield of the return) should contract money supply as depositors turn to Bitcoin holdings. Second, the proxy index for measuring exchange rate stability (ERS) would be:

$$ERS_t = \frac{0.01}{0.01 + stdev[\Delta\,(\text{exchange rate})_t]}$$

For the construction of this index, we take the standard deviation of the daily change over two trading days. Third, in related literature there is less consensus on the financial openness (capital mobility, CMO) proxy which is the subject of considerable debate (Chinn & Ito, 2008). We contribute with the first attempt to build a *de facto* proxy, for the Stablecoin case wherein the next two proposed sub-indexes are averaged. (i) cmo1: where (n) are the number of pairs (markets) listed in digital exchanges involving the Stablecoin in question. (ii) cmo2: where (V) is the percentage of exchange volume over supply in circulation. We arbitrary construct the cmo1 index by also including data (from coinmarketcap.com) for other cryptocurrencies (10 in total, not presented here). The intuition is that the higher the number or available pairs, the more open to capital mobility the Stablecoin is. Unfortunately, the index does not change over time due to lack of available time-series and it is normalized to take value in the range of [0,1] using the feature scaling. The max number equals to 400 pairs (case of Bitcoin) and min equals to a non-zero positive integer according to latest available data. USDTether has almost as much markets (pairs) as Bitcoin and for that we derive a value of 0.95 for this cmo1 index. TrueUSD is close to USDTether in terms of liquidity (we assign the value of 0.90) while for DAI (value of 0.1) and SBD (value of 0.05) available pairs in exchanges are considerably less. This index lacks quantitative precision, yet it can be adequately used for this working and further developed in the future.

The second indicator is calculated as the percentage of daily trading volume with foreign markets (other pairs) as reported in digital exchanges over the available supply in circulation (M). This arguably captures the level of capital openness with external markets for that the transactions are executed in pairs with other assets. By way of example, for Bitcoin this indicator does not include bitcoin for bitcoin transactions. Daily trading volume with foreign markets is calculated as the product of trading volume expressed in US dollar (Q) times the exchange rate closing price. In the quantity theory of money context, this measure corresponds to the velocity of money, thus $V_t = \frac{P_t Q_t}{M_t}$. The logic is that the nominator shows the degree of interaction with the foreign exchange markets in relation to the monetary base. An asset with low trading volume in digital exchanges with regards to the overall monetary base would either imply excessive hoarding or simply what we are looking for. Thus, evidence of limited interaction with foreign markets.

Hence, we propose:

$$CMO_t = average\left(\frac{n - n^{min}}{n^{max} - n^{min}}, \frac{V_t - V_t^{min}}{V_t^{max} - V_t^{min}}\right)$$

## 4.5 The model & estimation

We use a sample with data (from coinmarketcap.com) spanning from 1 October 2016 to 1 April 2020 for the four representative Stablecoins corresponding to the proposed taxonomy. All pairs are against the US dollar.

As per April 2020, with market capitalization of US dollar 6,3 billion, the USDTether is ranked 4th after Bitcoin, Ethereum, Ripple whereas the market value of TrueUSD is close to US dollar 130 million, of DAI is US dollar 15 million (in the same ecosystem, MakerDAO value is US dollar 350 million) and of SBD is close to US dollar 6 million (in the same ecosystem, STEEM value is close to US dollar 70 million). Basic descriptive statistics for the Stablecoins in question are summarized below.

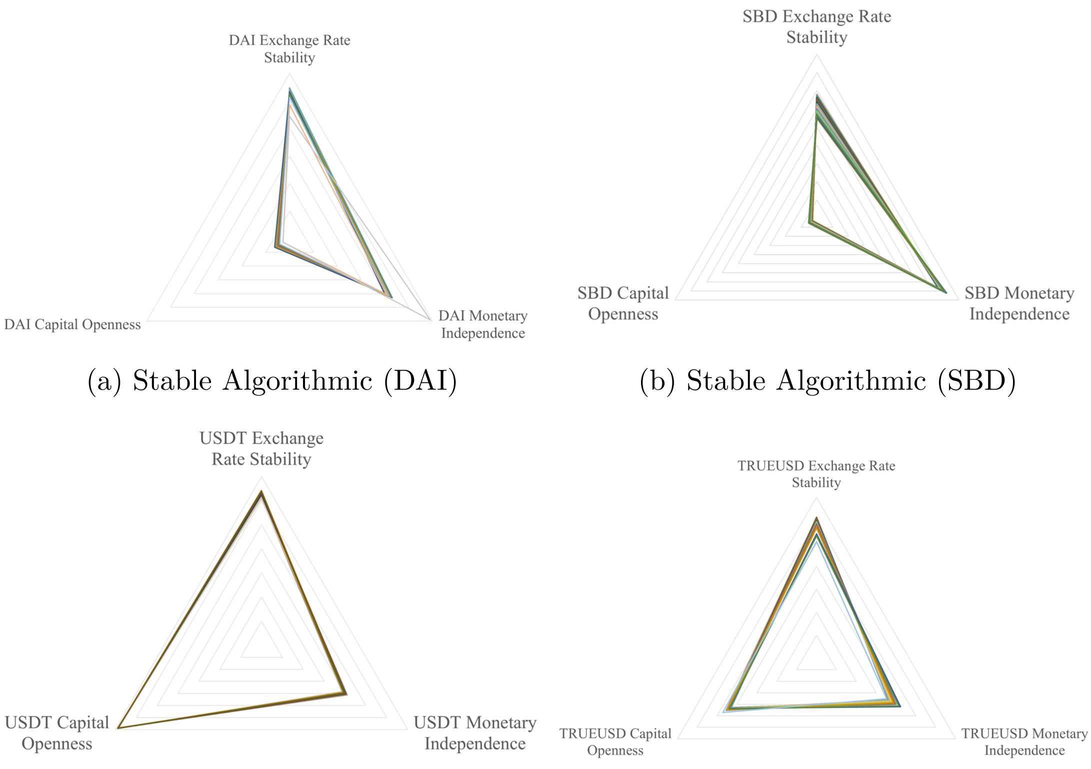
Exhibit 4.4: Summary statistics

| **Cryptocurrency (variable)** | **Obs.** | **Mean** | **Std. deviation** | **min, max** |
|---|---|---|---|---|
| DAI (Monetary Independence) | 795 | 0.4102 | 0.1870 | 0.0021, 0.6931 |
| DAI (Exchange Rate Stability) | 795 | 0.5284 | 0.1401 | 0.1600, 0.6931 |
| DAI (Capital Openness) | 795 | 0.0481 | 0.0401 | 0.0273, 0.4238 |
| SBD (Monetary Independence) | 1,279 | 0.3852 | 0.1941 | 0, 0.6929 |
| SBD (Exchange Rate Stability) | 1,279 | 0.3387 | 0.1923 | 0.0024, 0.6931 |
| SBD (Capital Openness) | 1,279 | 0.0136 | 0.0577 | 0, 0.4054 |
| USDT (Monetary Independence) | 1,279 | 0.3872 | 0.2004 | 0.0015, 0.6930 |
| USDT (Exchange Rate Stability) | 1,279 | 0.6135 | 0.1097 | 0.1745, 0.6931 |
| USDT (Capital Openness) | 1,279 | 0.6895 | 0.0301 | 0.4054, 0.6931 |
| TrueUSD (Monetary Independence) | 757 | 0.3650 | 0.1932 | 0, 0.6928 |
| TrueUSD (Exchange Rate Stability) | 757 | 0.6093 | 0.1138 | 0, 0.6931 |
| TrueUSD (Capital Openness) | 757 | 0.4545 | 0.0536 | 0.3867, 0.6791 |

The figures that follow show a graphical analogue of the Impossible Trinity across time. Note that for the purposes of this illustration the monthly average for each indicator was computed.

We observe that all Stablecoins drift towards exchange rate stability as anticipated. First, Stable Tokens (USDT, TrueUSD) are characterized by high levels of capital mobility and large amounts of reserves in foreign assets. This exchange rate arrangement is said to mimic the self-regulatory mechanism of *Currency Board Arrangements* wherein

Exhibit 4.5: Configuration of the indexes in the panel and time dimensions




(a) Stable Algorithmic (DAI)

(b) Stable Algorithmic (SBD)

(c) Stable Token (USDT)

(d) Stable Token (TUSD)

the Stablecoin is backed by reserves only in foreign assets. The originator stands ready to exchange its cryptocurrency on demand for the anchor foreign currency at parity.

Furthermore, Algorithmic Stable (DAI and SBD) feature low openness presumably due to capital restrictions applied on their collaterized assets. Second, recall that in DAI Stablecoin, collateral assets are pledged and managed in securing price stability. In this case, the US dollar does not circulate, yet it is used as the anchor. Restrictions on the collateral funds apply as exchange rate stability is maintained via reserves management monitored by the Smart Token holders. Note that DAI Stablecoins are created by locking other crypto-assets collateral on smart contracts. This mechanism creates derivatives in the form of Collateralized Debt Positions (CDP in short) permitting leverage investments (trading on margin) in a decentralized fashion, thus not via a trading firm. The value of the crypto-asset collateral is reported by the Smart Token's holders (MKR) who feed the system with prices (spot exchange rates of these collateral) aiming to meet a reserve requirement ratio, usually 150 per cent over the collateral. By way of example if the current value of the collateral is 150 US dollar, the depositor can raise up to 100 DAI (thus, 100 US dollar). Third, SBD Stablecoin is pegged to the US dollar at parity. Again, the US dollar does not circulate. It is, however, convertible on demand to the Altchain cryptocurrency (STEEM). This has a more liquid (deep) market with the US dollar playing the role of "digital gold" for storing value. It is in this connection that the Stablecoin is indirectly convertible to its price anchor. It follows from this that the Exchange Standard, an exchange rate arrangement belonging to the varieties of the Gold Standard (Diebold et al., 1991) whereby a currency is convertible to the US dollar which is by law convertible to gold, is another International Finance practice employed by Stablecoins. In more detail, the Stabelcoin (SBD) which intends to play the role of means of payment in the ecosystem is convertible at the prevailing spot exchange rate STEEM / US dollar (holders' of another, a third non-tradeable domestic cryptocurrency called Steem Power feed with prices). Note that STEEM holders may suffer from dilution Gold Standard alike if the price of this asset (digital commodity) plunges.

The graphical analyses, however, don't allow us to capture how "binding", thus linear, is the underlying "trade-off" theory. To do so, we estimate the next linear-log specification which is preferred to the baseline linear-linear model based on the AIC information criteria (not presented).

$$1 = a_j lnMI_{i,t} + b_j lnERS_{i,t} + c_j lnCM_{i,t} + e_{i,t} \tag{4.1}$$

We followed the R. Davidson & MacKinnon (1981) methodology in testing both models and eventually selected the linear-log specification (comparison data not presented) though with minor differences on the basis of higher $R^2$ and the AIC criterion. Both models display high F-test which rejects the hypothesis that the models (the estimated coefficients) are zero (not presented here). We turn now to elaborate on the model's philosophy. The inherent binding assumption is that the three policies are related in a linear manner resulting to in-between trade-offs in choosing a weighted average combination of two policies. If the Impossible Trinity hypothesis is supported, then estimated values should move around unity and estimated errors show how much of the three policies are not fully utilized. In other words, how much the trinity is apart from the binding assumption. Low goodness-of-fit (Rsquared) of the model suggests that either the model is wrong (trinity and trade-offs) or the relationship between the three variables is non-linear (Canale et al., 2018). The next table presents the results. Note that contribution (weight) is the estimated coefficient times the sample mean.

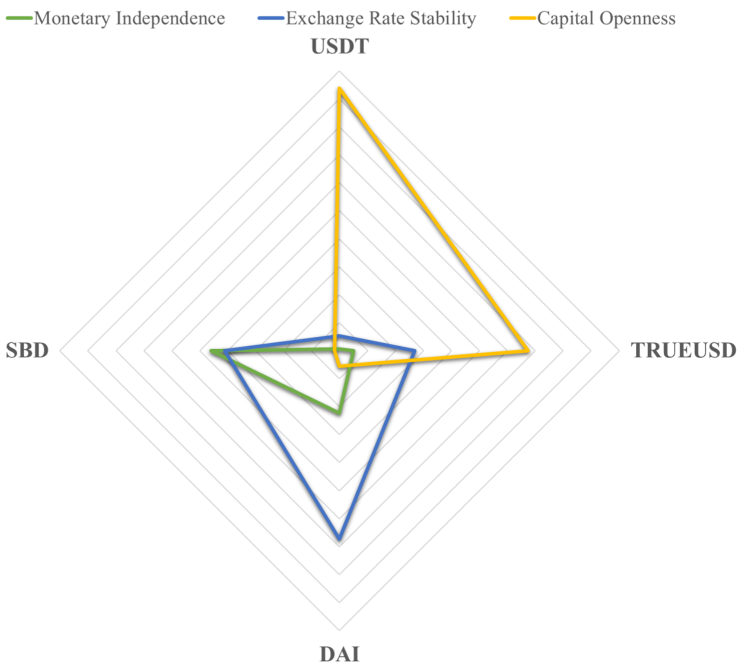
Exhibit 4.6: Table of estimations

| Asset | Variable | Sample mean | Est.coefficient | Std.error | Contribution | Rsq. |
|---|---|---|---|---|---|---|
| DAI | MI | 0.410 | 0.541*** | 0.034 | 0.222 | 0.9516 |
| | ERS | 0.528 | 1.274*** | 0.031 | 0.673 | |
| | CMO | 0.048 | 1.162*** | 0.294 | 0.056 | |
| SBD | MI | 0.385 | 1.193*** | 0.032 | 0.460 | 0.8876 |
| | ERS | 0.339 | 1.213*** | 0.027 | 0.411 | |
| | CMO | 0.014 | 1.272*** | 0.173 | 0.017 | |
| USDT | MI | 0.387 | 0.015*** | 0.022 | 0.006 | 0.9982 |
| | ERS | 0.614 | 0.088*** | 0.006 | 0.054 | |
| | CMO | 0.690 | 1.361*** | 0.021 | 0.938 | |
| TUSD | MI | 0.365 | 0.136*** | 0.440 | 0.050 | 0.9911 |
| | ERS | 0.609 | 0.440*** | 0.136 | 0.268 | |
| | CMO | 0.455 | 1.482*** | 0.1482 | 0.674 | |

*Notes: Robust errors (*) significant at 10 %; (**) significant at 5%; (***) significant at 1%.*

All stablecoins fit in the Impossible Trinity assumption for that all models display high $R^2$. The next figure graphically depicts the estimated contributions.

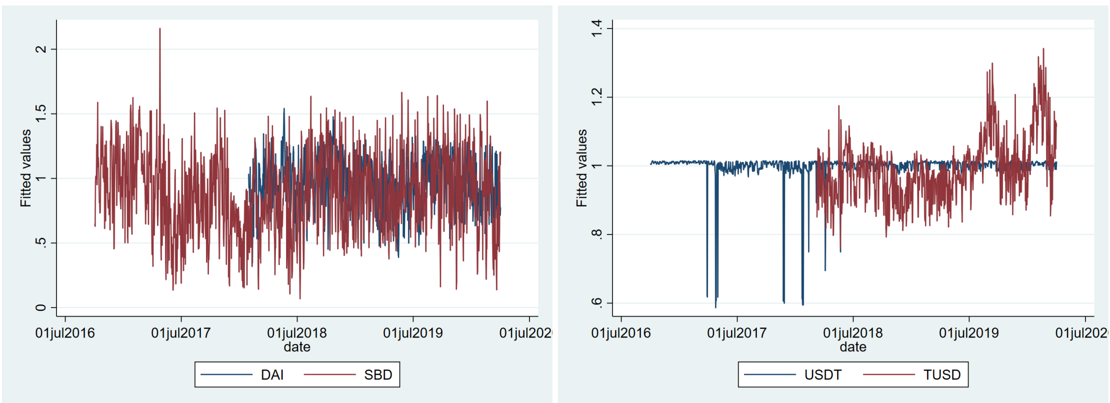
Exhibit 4.7: Estimated contributions (weights)



It is evident from the above results that in Stable Algorithmic the exchange rate stability and monetary independence estimated contributions (weights) prevail over the capital openness factor. The findings support our earlier attempt to distinguish Stablecoins on the basis of International Finance arrangements for that DAI and SBD as expected exhibit restrictions in capital mobility. In contrast, in Stablecoins under the *currency board regime* such as USDTether and TrueUSD the size of capital openness drives their success since they operate as electronic banks in facilitating cryptocurrency trading in digital exchanges. Hence, the role of monetary independence is extremely limited and questionable for these Stable Tokens, so far, are not associated with the real economy and explicit macroeconomic targets.

The linear relationship between these variables can be graphically interpreted as the tendency of the fitted value to drift around unity while the prediction errors show where the theory is not "binding", thus how much of these objectives is not fully adopted (Aizenman et al., 2013). Overall, the Stable Algorithmic SBD has experienced substantial deviation from the value of 1 which is also the case to a lesser extent for the other Algorithmic Stable [DAI]. This can be attributed to their decentralized nature aiming to achieve consensus and stability on the basis of an algorithm compared to centralized Stable Tokens backed by the legal obligation for convertibility on demand by the private entity. The figure below presents the predicted values.

Exhibit 4.8: Display of fitted values




(a) DAI, SBD (b) USDTether, TrueUSD

To recapitulate, the model sufficiently captures the evidence of a weighted average combination of price stability and capital openness at monetary independence expense as the latter contracts and expands to meet the previous two objectives. Notable case is USDTether wherein the capital openness indicator approximates unity for the whole period examined, thus showing low evidence of trade-off. This should be, however, examined in conjunction to recent empirical evidence associating unusual trading activity in this particular cryptocurrency with Bitcoin price manipulation during periods of extreme hype (Wei, 2018a).

## 4.6 Robustness checks

Robustness analysis is divided into two main groups i.e use of alternative estimation methods and use of alternative indicators. The latter re-estimate with the same methods, though using alternative dataset and fall outside the scope of our analysis for that it is difficult to construct alternative proxies due to limited information that can relate cryptocurrencies with real economic activity. Contrary, the former group focuses on the estimation techniques for that the model specification in Equation (4.1), by construction, is exposed to three major limitations (Canale et al., 2018).

First, the endogeneity issue, thus the correlation between the disturbance error and explanatory variables since the model is forced to have only three independent variables and therefore possibly other relevant variables are omitted. Second, measurement errors which may arise due to the fact that the selected proxies are constructed and derive data from different in nature variables. Third, an incorrect functional form is possibly assumed in the proposed model. This being the case, the estimates turn biased and inconsistent. Next we perform two robustness analyses. We construct (a) alternative indexes and employ (b) alternative estimation methods.

Given the importance of constructing suitable indexes, we revisit the methodology employed in this empirical framework. First, we adjust the ERS index by calculating the standard deviation of the daily price using a time window of the last three days rather two. Second, in the CMO index we drop the cmo1 sub-index and, therefore, we only use the cmo2 sub-index which monitors the change in daily volume (in USD). Thus, the daily interaction of the Stablecoin with traditional money markets. In last, the variable employed for the construction of the MI index is importantly altered. Instead of Bitcoin, we examine the interaction of Stablecoins with another asset of major importance. This is the US dollar to which are supposedly pegged to. In this frame, we derive data (from Stlouisfed.org) for the Overnight London Interbank Offered Rate (LIBOR), based on US dollar. This is the average interest rate at which selected banks borrow funds from other banks in the London market (for the non-trading periods such as weekends we used linear interpolation to generate values which is open to discussion). Since, Libor is a widely accepted "benchmark" or reference rate for short term interest rates it is logic to assume that Stablecoins have linkages with USD interest rates. Descriptive data (not presented) support this selection as all Stablecoins which are pegged to the US dollar at parity and in turn, the US money-market asset exhibit non-negative correlation.

Again, the results in the next table confirm our initial findings, particularly for the Algorithmic Stable. For the USDTether, the estimated trade-off among the indexes improves in quality (contribution of CMO lowers while ERS increase) whereas for the TrueUSD the weights slightly change but without altering their initial interpretation.

Exhibit 4.9: Table of estimations (alternative indexes)

| Asset | Variable | Sample mean | Est.coefficient | Std.error | Contribution | Rsq. |
|---|---|---|---|---|---|---|
| DAI | MI | 0.3964 | 0.4329*** | 0.0323 | 0.1716 | 0.9505 |
| | ERS | 0.4946 | 1.5701*** | 0.0292 | 0.0422 | |
| | CMO | 0.0044 | 0.4593 | 0.8319 | 0.002 | |
| SBD | MI | 0.3853 | 1.4376*** | 0.032 | 0.4323 | 0.8729 |
| | ERS | 0.2884 | 1.122*** | 0.0283 | 0.4146 | |
| | CMO | 0.0015 | 1.272*** | 0.0401 | 0.023 | |
| USDT | MI | 0.3828 | 0.0822*** | 0.078 | 0.0315 | 0.9907 |
| | ERS | 0.5941 | 0.4416*** | 0.0205 | 0.2624 | |
| | CMO | 0.6581 | 1.0584*** | 0.0771 | 0.6965 | |
| TUSD | MI | 0.3638 | 0.262*** | 0.0259 | 0.0953 | 0.9721 |
| | ERS | 0.5873 | 1.4202*** | 0.0221 | 0.8341 | |
| | CMO | 0.166 | 0.2545*** | 0.0621 | 0.0422 | |

*Notes: Robust errors (*) significant at 10 %; (**) significant at 5%; (***) significant at 1%.*

In addition, we estimate again the selected model by means of an alernative estimation methods namely the two-stage least squares (2SLS). Following the standard procedures in the literatue as highlighted in Canale et al. (2018), we use as instrumental variables the lagged observations for the CMO and MI indicators. The results in the table below support our initial findings.

Exhibit 4.10: Table of estimations (2SLS model)

| Asset | Variable | Sample mean | Est.coefficient | Std.error | Contribution |
|---|---|---|---|---|---|
| DAI | MI | 0.4102 | 0.5522*** | 0.0344 | 0.2265 |
| | ERS | 0.5284 | 1.2621*** | 0.0315 | 0.6668 |
| | CMO | 0.0481 | 1.2142*** | 0.2908 | 0.0584 |
| SBD | MI | 0.3852 | 1.1923*** | 0.0271 | 0.4592 |

| | | | | | |
|---|---|---|---|---|---|
| | ERS | 0.3387 | 1.2122*** | 0.0314 | 0.4105 |
| | CMO | 0.0136 | 1.3437*** | 0.179 | 0.0182 |
| | MI | 0.3872 | 0.0206*** | 0.0064 | 0.0079 |
| USDT | ERS | 0.6135 | 0.0863*** | 0.0218 | 0.0529 |
| | CMO | 0.6895 | 1.359*** | 0.0208 | 0.937 |
| | MI | 0.3650 | 0.1238*** | 0.0163 | 0.0451 |
| TUSD | ERS | 0.6093 | 0.4398*** | 0.0273 | 0.2679 |
| | CMO | 0.4545 | 1.4918*** | 0.0425 | 0.6780 |

*Notes: Robust errors (*) significant at 10 %; (**) significant at 5%; (***) significant at 1%.*

Finally, we assessed the possibility of using cointegration tests as an alternative estimation method widely employed in the literature (Aizenman et al., 2013) in showing evidence of the linearity of the three indexes for each Stablecoin. We conducted the Augmented Dickey-Fuller test but the results are inconclusive. The Monetary Independence index across all assets strongly rejects the hypothesis of non-stationarity while most of the rest indexes fail to reject the null hypothesis of unit root. As a result, we did not formally proceed with cointegration tests, yet we did identify when tested in pairs (not presented here) that the non-stationary series of Exchange Rate Stability and Capital Openness for both Stable Tokens (USDTether and TrueUSD) cointegrate. This is in accordance with the earlier findings of evidence of high weights in these monetary objectives for Stablecoins under *currency board regimes*.

## 4.7 Conclusion

This paper applied the empirical framework of Impossible Trinity to the monetary analysis of Stablecoins. We showed that the trade-off of the degree of achievement along the three dimensions postulated by this hypothesis varies in accordance to the inherent monetary structures of each asset-class of Stablecoins. In particular, USDT and TrueUSD adhere to the Bullion Standard (Currency Board Arrangements) while SBD and DAI to the Exchange Standard and to the Reserve Standard respectively. In this work we do not used a complete catalogue of all the available Stablecoins rather a complete catalogue of all the possible asset classes of Stablecoins. A broader sample to further examine alternatives of this framework is proposed. Lastly, enrichment of the robustness analysis by constructing additional proxies, possibly building time-series for our proposed cmo1 sub-index and using additional estimation methods is recommended.

# Chapter 5

# Innovation Finance beyond Bitcoin: Cryptocurrencies as Alternative Investments

Over the past two decades, the diffusion of technological innovations introduced to the finance industry has been inconceivable. Inter- net, at the end of the 20th century, brought e-commerce, later e- payments and more recently e-money. Such innovations in digital world increase the impact on the business world, and so might do cryptocurrencies as alternative investments, currently spreading out across the globe. To this end, this chapter builds up an across the board synthesis of current theories and investment practices in cryptocurrencies alternative asset markets.

## 5.1 Introduction

When reflecting upon the recent developments in alternative finance, there is nothing more, no doubt, that has intrigued academics, investment professionals, institutions and the general public than the next brand new asset class that did not exist a decade ago namely *cryptocurrency*. But why is it called this way? More importantly why is it an investment and in particular an alternative one? And, be that as it may, then what kind of alternative investment? These fundamental questions will be approached by this chapter.

The first ever cryptocurrency was proposed by the pseudonymous Satoshi Nakamoto back in 2008 in a paper made publicly available on an internet forum. Note that the term *cryptocurrency* never appears in the original paper. It is not a term coined by the creator of Bitcoin rather it emerged later on by community members. It is argued that Satoshi Nakamoto interest was to invent the first payment system without intermediary (the Blockchain) rather than a revolutionary currency *per se* (the Bitcoin). Interesting enough, note that the title of his work underlines the *cash system* rather the *asset* wherein he decided to name it after the latter (Bitcoin: A peer-to-peer electronic cash system). Such cash systems operating via peer-to-peer (open) networks epitomize the new concept branded as socialization of Finance. In principle, the centerpiece of this sophisticated breakthrough is its potential to *be programmed to record virtually everything of value and importance to humankind* (Tapscott & Tapscott, 2016).

The remaining of this chapter is organized as follows. The next section offers historical events. Then, current investment practices in cryptocurrency markets are presented. The last sections discuss imitations, challenges and research the way forward.

## 5.2 Background

The parameters which build the supply side of each cryptocurrency vary, though most variables are common in nature. In the most popular case called Bitcoin these are the following:

- bitcoins (with lowercase): are the native assets divided down to 8 decimal places with the smallest unit named satoshi in homage to the original creator, Satoshi Nakamoto. Hence, 1 bitcoin equals to 108 satoshi. In the protocol that regulates the supply schedule of bitcoins, the main rules are as follows:
- Total supply capped at 21 mil units,
- New units come out every 10min which is approximately the time required to settle a block. A block is like a page of a ledger where the newly validated transactions are recorded and added to the previous block creating a chain of blocks, thus the blockchain.
- New units are created at a rate which is increasing at a decreasing rate every 210.000 blocks, thus approximately every four years is cut in half. Note that the first block issued 50 bitcoins and today (as per July 2019) is 12,5.

It is curious thing, worthy of mention, that cryptocurrencies play a dual role i.e. payment within their own payment system (the Blockchain) and investment.

- Payment: Agents use cryptocurrencies for payments of goods. Hileman & Rauchs (2017) distinguish between two categories of such payments. *payment rail* whereby cryptocurrencies stand for a channel for that they simply *play the role of a means to an end*, thus money exit the crypto finance ecosystem taking benefit from faster, cheaper and anonymous transfer of sovereign currencies. *cryptocurrency payments* whereby they are used to pay for a service or a good delivered, thus money stays in the ecosystem.

- Investment: Agents enter into investment transactions by storing cryptocurrency value with the purpose of gaining benefit in the form of realized / unrealized capital gain in the future. This chapter focuses on this role.

But if cryptocurrencies are currencies, then why they are not part of traditional investments and cash? An easy argument would be that currencies are only supplied by sovereign authorities. But this is not persuasive enough. Back in 2009, Bitcoin was the first but today it is not the only cryptocurrency in town. In this empirical work, we shift attention to the next four categories of cryptocurrencies. We draw a sample with present-day market leaders (in the parenthesis).

1. Bitcoin, the overall market leader.

2. Altcoins (LiteCoin) running on a built-in "first wave of innovation" blockchain: They are either created (a) from scratch by replicating the open-source code of Bitcoin or (b) as spin-offs (called hard forks)[1] from the original Bitcoin network.

3. dAppcoins (Ethereum) running on a built-in "second wave of innovation" blockchain. Also referred to as Altchains.

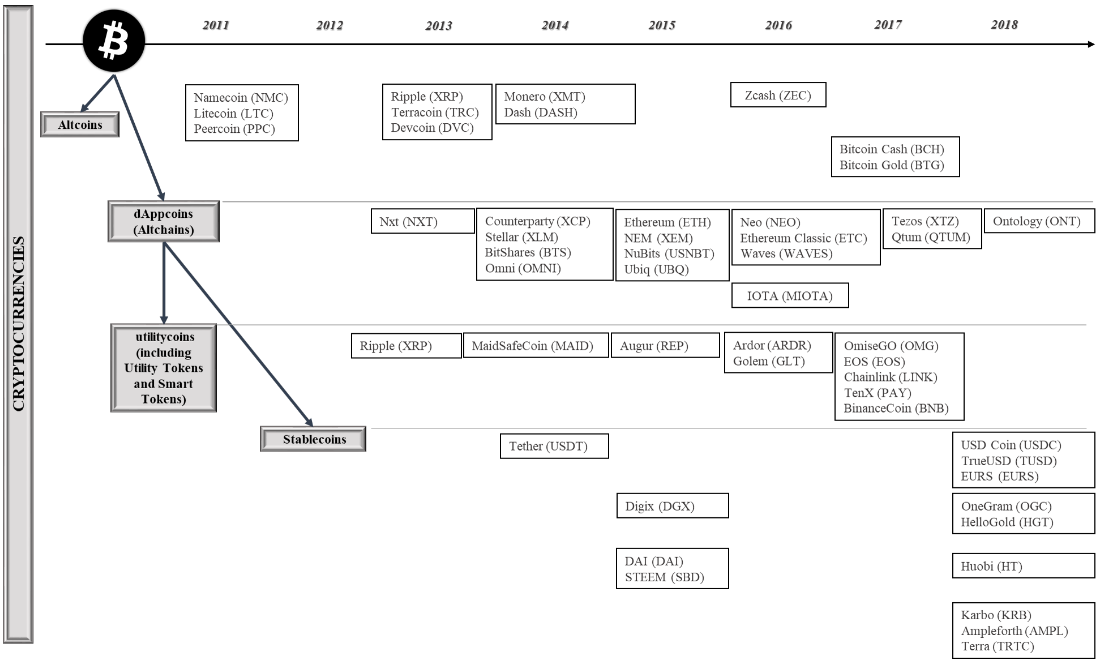
4. Utilitycoins (Binance) usually running without built-in Blockchain, thus on top of second wave Blockchain innovation. These mostly refer to Utility Tokens for that they are usually issued by a legal entity. For the purpose of this analysis we do not differentiate this category from Smart Tokens.

5. Stablecoins (USDTether) which follow fixed exchange rate arrangements.

[1]Thus far, there have been released almost 50 update versions of the Bitcoin software. Since 19/3/2014 has been renamed Bitcoin Core (available at www.bitcoin.org) and is the reference implementation (client) of Bitcoin nodes, which form the Bitcoin network. Changes (updates) are subject to voting. The way wherein the nodes that have downloaded the software exercise this voting right is by following, or ignoring the recommended change by the community. If the former is the case, then this results to what is called *forks*.

Altogether, the next figure below collects and classifies on the basis of the above taxonomy 50 selected cryptocurrencies throughout the last ten-year trading history (the trading ticker in parenthesis).

Exhibit 5.1: Evolution of the cryptocurrency universe over the last ten years




The higher number of tokens demonstrate the rapid growth in this class due to the easiness of developing tokes for that they use an already available blockchain for their initial offerings and subsequent recording of transactions.

### 5.2.1 Market history & institutional watchdogs

It is apparent from the historical standpoint of view, there have been quite a lot significant events after the release of Bitcoin in 2009. These are summarized as follows:

- 2008: The domain name bitcoin.org is registered by Satoshi Nakamoto.
- 2009: Bitcoin network is uploaded. Bitcoin price is effectively close to zero.
- 2010: The first private digital exchange listing Bitcoin goes live. Its name Bitcoinmarket.com
- 2011: The first transaction with bitcoins as a means of payment for the purchase of a real good in the economy takes place. According to Yermack (2013) who actually

quotes Wallace (2011) the object of acquisition was two pizza procured at a cost of 10,000 bitcoins in 2009: the pizza parlor did not accept bitcoins directly, and instead a third-party broker was enlisted who agreed to procure the pizza using a credit card (based on a real currency) and accept the bitcoins, worth almost 5 million at recent prices, as consideration. (Yermack, 2014)

- 2011: Namecoin becomes the second cryptocurrency and first altcoin. That year and for the first time after two years of trading, Bitcoin takes parity with US Dollar.
- 2014: Three key events occur as 1 bitcoin trades between USD 300 and USD 800.
- 2014: Nxt becomes the first altchain (and dAppcoin) to allow other assets to be issued and circulated on its blockchain
- 2014: A new and controversial procedure to raise capital named Initial Coin Offerings (abbreviated ICO) and Initial Token Offerings (abbreviated ITO) enters the crypto-scene. The first ever that took place was by the cryptocurrency labeled *Counteryparty* on February, 3 in 2014 (close date of the ICO) whereby USD 1,79 mil were raised in exchange for the crowd-sale of specific units of this cryptocurrency.
- 2014: MaidSafeCoin becomes the first token running on another surrogate blockchain.
- 2015: Tether becomes the first stable cryptocurrency issued by a private company enabling the concept of IOU obligation of the cryptocurrency issuer. That year 1 bitcoin continues to trade less than USD 1.000.
- 2017: In late 2017, Bitcoin reaches the all-time peak (USD 20.000). In December of that year, two US based Exchanges namely the Chicago Mercantile Exchange (CME) and the Chicago Board Options Exchange (CBOE) launch the first Bitcoin futures contracts opening the market to institutional investors.
- 2018: End of December that year, the creators of the *Basis project*, a new Blockchain wherein three cryptocurrencies co-exist i.e. Basis stablecoin, Basis Shares and Basis Bonds issue an emotional statement announcing that they are obliged to cease their operations. The reason is that US authorities characterized the two latter assets as *unregistered securities* and that the team would have to apply US securities regulation to the system which among others does not permit the sale of these

assets for at least one year. Eighteen months earlier, Basis project had raised USD 133m. The team announced that they will return what is left to investors.[2]

Bitcoin's increasing hype had regulators on the toes. It was only a matter of time for institutional authorities to show interest in formally examining cryptocurrencies and in some cases even take actions. In Europe, the European Central Bank (ECB) was the first institution to be concerned with. In October 2012, ECB issues a 55-page report on virtual currencies schemes,[3] only to deduce that they pose no risk to price stability in the real economy due to (a) their low volume traded, (b) lack of wide acceptance and (c) limited connection to real assets. Of course, as expected ECB underscores the hazard of illegal transactions through crypto-currencies and for that reason accolades the role of centralized real currency and payment systems.

In early 2013 in the United States, the Financial Crimes Enforcement Network (FinCEN) and the Stock-Exchange Commission (SEC) openly acknowledged Bitcoin as *convertible virtual currency.* On the contrary, the Chinese Government declared that Bitcoin *is not even a currency* and in effect banned its commercial use. It is not peculiar that countries in which Bitcoin has been officially banned are mostly centralized in one way or another i.e. Vietnam, Thailand, Bangladesh, Sweden, Russia, Iceland, Bolivia, India, Ecuador and China as said.

During the same period, SEC issued a public statement for investors being preoccupied that crypto-currencies "may lure investors to fabricated transactions" (released on 23/07/2013). By that time, US agencies complete in-depth investigations leading virtual currencies to seizure and even corporate executives to sentence. Major examples that raised polemic were *Liberty Reserve* and *e-gold.* In late 2014, a federal judge in the United States sentenced a Bitcoin entrepreneur for easing illegal transactions (drugs) via Silk Road, an online black market where products are denominated and paid in bitcoins.

In the United Kingdom in September 2014, Bank of England released a study on the potential risks and benefits of crypto-currencies.[4] The findings bears a resemblance to ECB's i.e (i) they do act as money though to a limited extent for relatively few people, (ii) the economics of the scheme both at micro and macro level pose challenges and (iii) they do not pose a material risk to monetary or financial stability in the UK. In 2015, the Euro Banking Association (EBA) launched an exhaustive study on crypto-technologies recognizing four major manifestations namely currencies, asset registries, application stacks and asset-centric technologies.

[2]The statement can be found here: https://www.basis.io

[3]ECB: "Virtual currency schemes"

[4]Bank of England. Quarterly Bulletin 2014 Q3. The economics of digital currencies (2014).

In late 2015, The Court of Justice of the European Union has ruled that the services of a Bitcoin exchange in exchanging Bitcoin for a traditional currency is exempt from value added tax on the basis of the *currency exemption*.[5]

In 2017, in the United States of America, SEC announces that tokens are securities whether are purchased using U.S. dollars or virtual currencies and thus now subject to federal securities laws. Later that year, Bitcoin derivatives are launched but trading volume is considerably, though regulators still explore the approval of listing Exchange Traded Funds and exchange products in general holding cryptocurrencies. Another concern for regulators is Initial Coin Offering procedures and so far only some guidelines in the form of questions have been submitted to the investment public.

### 5.2.2 Current research trends on cryptocurrencies as alternative investments

Current research is interested in the legal, technological and finance / economics aspects of cryptocurrencies. In the micro-financial economics firmament, the main strand of literature revolves around the demand-side of cryptocurrencies and the main puzzles are price formation, volatility and possible empirical anomalies. In other words, research examines cryptocurrencies' behavior as an investment asset. Under this frame, preliminary studies probe into the profile of cryptocurrencies' investors. For Grinberg (2012) the holders of bitcoins vary including early adopters, enthusiasts, criminals, speculators, online merchants such as web hosts, casinos, illicit drug marketplaces, auction sites, NPOs and adult media.

The area that receives the greatest attention examines the underlying users' demand motives, thus whether demand cryptocurrencies for speculation (store of value) or for facilitating transactions (medium of exchange). First research studies in this field (Barber et al., 2012) had very early identified volatility, legislation influence, anonymity, availability (number of subjects accepting payments) and awareness (media impact) to be notable demand factors. Buchholz, Delaney, Warren, & Parker (2012) and Glaser et al. (2014) empirically test the relationship between Bitcoin price and queries on search-engines to find that attractiveness for investors is a key factor for price formation.

In the last years the leading strand of literature probes into identifying trading patterns. It is worth adding that, given their generally observed inclination to high volatility, cryptocurrencies' have been lately excessively examined to be uncorrelated

[5] See, "Judgement in Case C-264/14. Skatteverket v David Hedqvist". Press Release No 128/15, Luxembourg, 22 October 2015

with all other financial classes Kajtazi & Moro (2019); Corbet et al. (2019) making them suitable for portfolio diversification purposes but not for hedging as Bouri et al. (2017) conclude in their empirical work. Dyhrberg (2016b) argues that Bitcoin may be *useful in risk management and ideal for risk averse investors in anticipation of negative shocks to the market*.

Finally, Griffin & Shams (2018) stretch the point that in the case of Bitcoin, bearish prices may be associated with blur trading strategies involving privately controlled digital currency exchanges and related cryptocurrencies such as Tether (USDT). Since 2018, the cryptocurrency Tether which is 1:1 pegged to the US dollar has replaced the US dollar as the most trade-able pair with Bitcoin leader. This means that such stablecoins offer the advantage of crypto-for-crypto trading while a traditional currency exists as an anchor. Lately this new strand of literature is growing as more stable cryptocurrencies pop up for that their absence of volatility gives a ground for considering possible integration with the traditional monetary system. This means that stablecoins do not have any investment interest for that they only mimic the variation of traditional currencies.

## 5.3 Cryptocurrencies in investment practice

This section explains how investments funds flow to this market both indirectly (to the ecosystem) and directly (to the asset).

### 5.3.1 Investing in the ecosystem: The cryptocurrency sectors

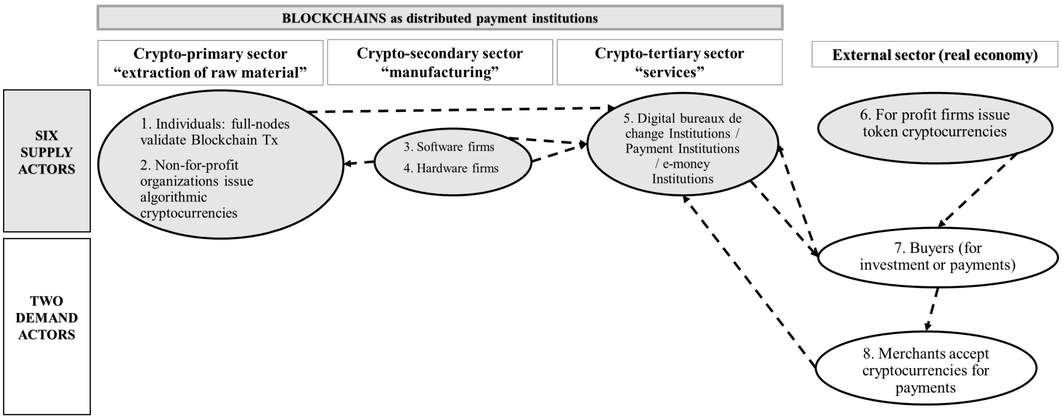
Distributed Ledgers spotlight a constellation of ecosystems covering all traditional sectors of economic activity. The Bitcoin hype has been so intense that the *cryptocurrency, blockchain project* was allegedly on the way to outpace in fundraising the entire 1995 internet project[6] as more and more crypto-finance startups have been clinching seed capital to craft innovative technological market products and services in this new ecosystem. From the industry perspective, investments to set up and finance firms operating in this ecosystem fall into the manufacturing and services sectors.

The next figure collects estimated data (2019) and schematically shows this.[7]

[6]See, article on Business Insider (2014). Available on http://www.businessinsider.com/the-future-of-the-payments-industry-2014-slide-deck-2014-7?op=1

[7]Annualized Bitcoin mining revenue is estimated at USD 6,5 bil by digiconomist.net. We arbitrary assume this to be USD 10 bil accounting for all algorithmic cryptocurrencies. According to Reuters, the Exchange market leader (called Coinbase company) realized USD 520 mil in sales

Exhibit 5.2: Sectors of economic activity in Distributed Ledgers ecosystems




| | Primary sector | Secondary sector | Tertiary sector | External sector |
|---|---|---|---|---|
| **Number of participants** | 1. Full-nodes=20.000 (Source: bitnodes, ethernodes)<br>2. Algorithmic CC issuers=850 *(Source: coinmarketcap)* | 3. Number of software firms=n/a<br>4. Number of hardware firms=n/a | 5. Exchanges=260 (Source: coin.market) | 6. Token CC issuers=1.500 *(Source: coinmarketcap)*<br>7. Number of buyers=40M wallets *(Source: news.bitcoin.com)*<br>8. Merchants=15.000 *(Source: coinmap)* |
| **Cash Flow model & motives** | 1. (1a) Receive new CC (minted/minted) paid in CC and (1b) receive fees for validating transactions (income paid in CC)<br>2. Placement of cryptocurrencies (capital received in CC) | 3. Receive proceeds from sale of software products (income paid in traditional currency)<br>4. Receive proceeds from sale of hardware products (income paid in traditional currency) | 5. Fees for exchanging CC (income paid in CC or traditional currency) | 6. Firms issue CC to lower cost of capital (capital received in CC)<br>7. Buyers sell CC (7a) for investment reasons (income from capital gains received in CC) and (7b) for paying for goods for that they receive better prices<br>8. Merchants use CC for lowering operating (Tx) costs |
| **Annual turnover** | Full-nodes income from mining: USD 10 bil (est. based on digieconomist) | n/a | Digital Exchanges income from fees: USD 2 bil (est. based on Reuters) | Investors income from capital gains: n/a |
| **Market value** | Asset Value of algorithmic CC=USD 275 bil *(Source: coinmarketcap)* | Equity Value of software / hardware firms=n/a | Equity Value of Digital Exchanges=USD 30 bil (est.) | Asset Value of Tokens=USD 25 bil *(Source: coinmarketcap)* |

What Blockchains actually do is to operate as distributed payment institutions through the active participation of all three sectors. Algorithmic cryptocurrencies constitute the backbone of the primary sector for that they fuel the operations of blockchains as payment systems. (Utility) Tokens are associated with the external sector and the real economy. Nonetheless, transactions of tokens are conducted via blockchains in the primary sector. It is true, however, that demand for cryptocurrencies within these sectors is substantially low or absent. This highlights the fact that these ecosystems rarely use cryptocurrencies as the functional currency. By way of example for paying salaries. We are now in a position to further elaborate on each sector.

and valued at USD 8 bil in 2018. We arbitrary assume that for the whole tertiary sector the figures are USD 2 bil and USD 30 bil respectively taken into consideration that this company holds approximately 22% market share according to data.bitcoinity.org. According to bitnodes and ethernodes full-nodes are close to 10.000 and 8.000 respectively. We arbitrary assume 20.000 in total.

### The crypto-primary (mining, minting) sector

The crypto-primary sector is concerned with the extraction of raw materials by analogy with the real economy. In the crypto-finance world this sector includes so far mining, minting and forging of Algorithmic cryptocurrencies. Individuals commit own resources such as hardware equipment, consumption of energy, bandwidth and there is only one reason for doing this; compete in validating transactions aiming to receive new cryptocurrencies and fees in return and finally profit by price appreciation. Usually they are natural persons (individuals) which “work” independently (e.g. self-mining) or cooperatively (the so-called pooling where computers contribute collectively their CPU/GPU and rewards are distributed analogously). Their role is imperative for the ecosystem just like the primary sector in the real economy for meeting basic needs.

### The crypto-secondary (electronics manufacturing) sector

The crypto-secondary sector is concerned with manufacturing by analogy with the real economy. Manufacturing firms develop two types of cryptocurrency products categorized as follows:

- hardware equipment including (a) machinery for efficient mining, (b) ATMs for cryptocurrency exchanges, (c) hardware wallets
- software equipment for cryptocurrencies including (a) online, (b) offline digital wallets sold on wholesale (to primary and tertiary sector) and on retail (thus, directly to end-consumers). Note that digital wallets are data files that store recorded transactions, outstanding balances and private keys. And (c) specialized software to include cloud-mining platforms to primary sector and trading platforms and mobile-wallets to the tertiary sector (exchange institutions) and of course the development of new Blockchains.

Here, investment strategy is substantial for that requires production of goods. The revenue model includes sale of products and subscription fees for services.

### The crypto-tertiary (financial services) sector

The crypto-tertiary sector is concerned with financial services by analogy with the real economy. Here, investment is even more substantial for that requires significant set-up, legal and marketing costs. This sector includes Initial Offering processes to raise investment funds and develop the project. In a more narrow view, crypto-financial services include (1) immediate exchange (1a) between traditional currencies and cryptocurrencies and (1b) only between cryptocurrencies, thus the digital bureau de charge institution does not deposit customer's money, (2) payments using cryptocurrencies and (3) e-money where licensed institutions store money by issuing electronic no-interest bearing deposits. It remains true, that credit institutions granting loans in relation to cryptocurrency assets are still absent. Most activity in this sector is conducted by exchanges which offer the following services: (a) wallets (usually for free), (b) exchange services (based on commission fees) and (c) Application Programming Interface (API), thus charge for market data.

Exchanges are market-makers for that they provide liquidity by closing the gap between buyers and sellers. In the much celebrated blockchain ecosystems' apolitical (distributed) spirit of cutting intermediaries, this stands for a critical violation. In its aftermath, it is through this sector that cryptocurrencies interact with other cryptocurrencies and with the well-established Foreign Exchange market and traditional currencies, and in turn indirectly regulate the cryptocurrency ecosystems. This happens because wallets are offered by private firms which require a license of electronic money institution (e-banks) issued and oversight by local central banks. Signing up and opening a wallet account would involve compliance with AML (Anti-Money laundering) / KYC (Know-Your-Customer) policies, and therefore the credential of "pseudonymous" transactions originally embedded into cryptocurrency philosophy cancels out. This means the owner and the path of tokens' transactions are utterly traced on the public ledger. Most digital exchanges operate double auctions with bids and asks prices stated and charge commissions while some offer more sophisticated trading tools.

### The external (real-traditional currency-economy) sector

The external sector constitutes the level of openness of the cryptocurrency ecosystems with the real economy. Many private Token initiatives have been drafted and some have lived up to to receive funding via Initial Offerings.

From the supply-side firms use the ecosystem by issuing token cryptocurrencies which grant the right to pay real goods offered by the originator (either via a digital platform such as trading firms or via the delivery of physical goods) in exchange for funds (received in other cryptocurrency). From the demand-side, only two actors are present. Buyers who have two motives i.e. (a) acquire cryptocurrencies for investment motives aiming to gain from price appreciation and (b) acquire cryptocurrency for payment motives for that they offer higher purchasing power compared with traditional cash.

Finally, merchants demand cryptocurrencies for that they prefer payments in this why compared to traditional cash because the former lower operating costs.[8]

### 5.3.2 Investing in the asset: The cryptocurrency markets

But what are the possible ways for an investor to enter into the cryptocurrency markets? It is certain that investment requires an initial outlay of capital. Investment placements to obtain the asset may take specific forms i.e purchased, mined and accrued.
**Exchanged:**

1. Purchased during an ICO process over the internet. For the period 2013-2018, studies (Boreiko & Sahdev, 2018) indicate that more than 1.524 ICOs were recorded. Accumulated ICO funds should be around USD 9 bil through this controversial open-finance procedure to invest in acquiring units of cryptocurrencies sold. The most successful ICO so far took place in June 2018 when *EOS* token completed a crowd-sale of USD 4,2 bil. A few months earlier *Telegram Open Network* token raised USD 1,7bil. In the 3rd place is *Tezos* token with USD 230 mil.

2. Purchased from a currency exchange that act as market-makers by offering liquidity or over-the-counter.
**Airdropped:**

3. (i) Mined, thus earned after the ICO process via a lottery competition. Miners are natural and legal persons acting as peers/full-nodes facilitating in validation of transactions that in turn enlarge supply and fall into two broad categories namely (a) self-mining, thus performed by individuals who "work" independently, (b) pool-mining, thus performed by a group of individuals by analogy with a co-operative scheme (usually a company is behind) where participants contribute collectively their CPU and rewards are distributed analogously. The downside of this is that decentralization (pure competition) is replaced by centralization (oligopoly) as concentration of computation power or hashrate in crypto terminology in a few mining-pools may enable manipulation of the blockchain.

4. Assumed holding a long position in the asset this receives an "interest" (like a saving deposit) on the cryptocurrency in the future as long as the investor does not dispose it. By way of example this is the case with Steem Power (SP), an

[8] There is a proliferation of applications of cryptocurrencies by the external sector for the issuance of Utility Tokens and include a variety of industries in the real economy. Only to enumerate a few: Energy, travel, gambling, financial services, entertainment and even controversial goods like cannabis.

internal non-tradable cryptocurrency created within the Steem-Blockchain that derives value from the Steem, tradable cryptocurrency. The pros of the SP asset is that it offers influence in participating in the Blockchain operations just like voting rights in shares. The cons of this SP is that it is not liquid in the sense that a holder for a specific period of time does not have the right to convert it to another Steem cryptocurrency which is tradable with sovereign currencies. This has the features of an equity.

Note that most mining activity takes place in China followed by Iceland, India, Georgia and Venezuela. There are two reasons for this concentration i.e cheap electricity and lax environmental policies. All the same, in this case investment is not substantial, thus opened even to natural persons as only requires to spend money in capital expenditures to acquire the appropriate technical equipment for mining while incur operating expenses during mining (e.g. electricity cost). Note that investments in Capital Expenditures serve as a key indicator that reflects future expectations on profitability and expansion of mining business. The revenue model is related to winning the mining-competition and receive the new units of the cryptocurrency or /and receive transaction fees by the participants for transacting via the blockchain.

### 5.3.3 General market information

Today, 10 years after Bitcoin the crypto-finance ecosystem features numerous cryptocurrencies traded over nearly 20.000 markets (pairs listed in exchanges) amounting to a total market capitalization of close to USD 300 bil and daily volume of approximately USD 60 mil. The next table provides a market overview of the top-15 traded assets.

In the first rank for ten consecutive years is Bitcoin but accompanied with two more hard forks of Bitcoin (altcoins). This highlights the trust of the investment community on the Bitcoin blueprint. The last column on the right shows how liquid the pair is, this in how many exchange markets is listed.

### 5.3.4 Understanding the cryptocurrency trading metrics

Trading cryptocurrencies embroils comprehension of particular metrics in this new market. Below, the most relevant that readers may find when look at platforms that trade cryptocurrencies:

- Ticker: Every cryptocurrency has a ticker symbol just like equities. Bitcoin's is BTC.

Exhibit 5.3: Table of cryptocurrency data (in USD, as per July 30, 2019)

| Name (launch year) | Market Cap in USD | Price in USD | Volume (24h) in USD | Circulating Supply & ticker symbol | Markets traded |
|---|---|---|---|---|---|
| Bitcoin (2009) | $169.610.819.668 | $9.504,21 | $15.705.735.089 | 17.845.862 BTC | >400 |
| Ethereum (2015) | $22.469.791.941 | $209,80 | $6.147.308.086 | 107.103.401 ETH | >400 |
| Ripple (2012) | $13.281.261.477 | $0,310073 | $935.656.506 | 42.832.704.971 XRP | >400 |
| Litecoin (2011) | $5.685.981.07 | $90,43 | $2.778.330.817 | 62.878.343 LTC | >400 |
| Bitcoin Cash (2017) | $5.494.789.807 | $306,65 | $1.453.443.707 | 17.918.563 BCH | 360 |
| BinanceCoin (2017) | $4.238.189.114 | $27,25 | $156.142.012 | 155.536.713 BNB | 214 |
| Tether (2014) | $4.020.260.813 | $0,998187 | $17.778.926.209 | 4.027.564.415 USDT | >400 |
| EOS (2018) | $3.849.595.240 | $4,16 | $1.919.570.068 | 925.266.655 EOS | 328 |
| BitcoinSV (2018) | $2.599.240.107 | $145,58 | $385.040.700 | 17.854.986 BSV | 135 |
| Stellar (2014) | $1.632.042.646 | $0,083196 | $89.018.251 | 19.616.918.913 XLM | 268 |
| Cardano (2017) | $1.579.285.245 | $0,060913 | $46.097.742 | 25.927.070.538 ADA | 92 |
| TRON (2018) | $1.462.619.944 | $0,021934 | $447.513.228 | 66.682.072.191 TRX | 245 |
| Unis Sed Leo (2019) | $1.338.006.381 | $1,34 | $6.831.275 | 999.498.893 LEO | 17 |
| Monero (2014) | $1.332.262.111 | $77,79 | $88.113.637 | 17.125.814 XMR | 128 |
| Dash (2014) | $941.289.336 | $105,20 | $346.464.445 | 8.947.392 DASH | 251 |

*Data Source: coinmarketcap, 2017-2019. Additional notes: *indicate that the asset is not mineable, thus the total supply equals circulating supply. **indicates that the asset is not mineable but the supply varies as the issuer controls the quantity.*

- Launch date: It is an indicative measure of how long the asset has been traded.
- Price: The price for each unit of cryptocurrency (which is further divided into decimals accordingly) expressed in another currency.
- Max supply: It is the amount of all units to be issued. There are two cases, thus capped (like Bitcoin and Ripple) and uncapped cryptocurrencies (like Tether). The former category is further distinguished between mineable and non-mineable supply.
- Mineable supply: Mineable cryptocurrencies are based on a consensus algorithm that governs the pre-determined change in supply. Non-mineable (or pre-mined) cryptocurrencies have all units of supply released. This is the case with Ripple and most of utilitycoins.
- Circulating supply: For cases like Bitcoin this is straightforward and it is always known how many units of the cryptocurrency has already been issued so far. However, in cases like Ripple this is open to debate. In this case, many of Ripple cryptoucurrencies that were pre-mined are deposited in an escrow account that Ripple Incorporation (the company that develops Ripple Blockchain) controls. It goes without saying that in such cases, supply and in its aftermath price can be manipulated.
- Volume: This is estimated in another currency and measured within a specified time frame (day, month). It represents how liquid the market is in terms of investment activity.

- Transaction count: In relation to volume, this metric states the number of transactions occurred within a specified time frame.

- Markets: Number of pairs of this cryptocurrency listed in digital currency exchanges. This number is a liquidity indicator of the cryptocurrency.

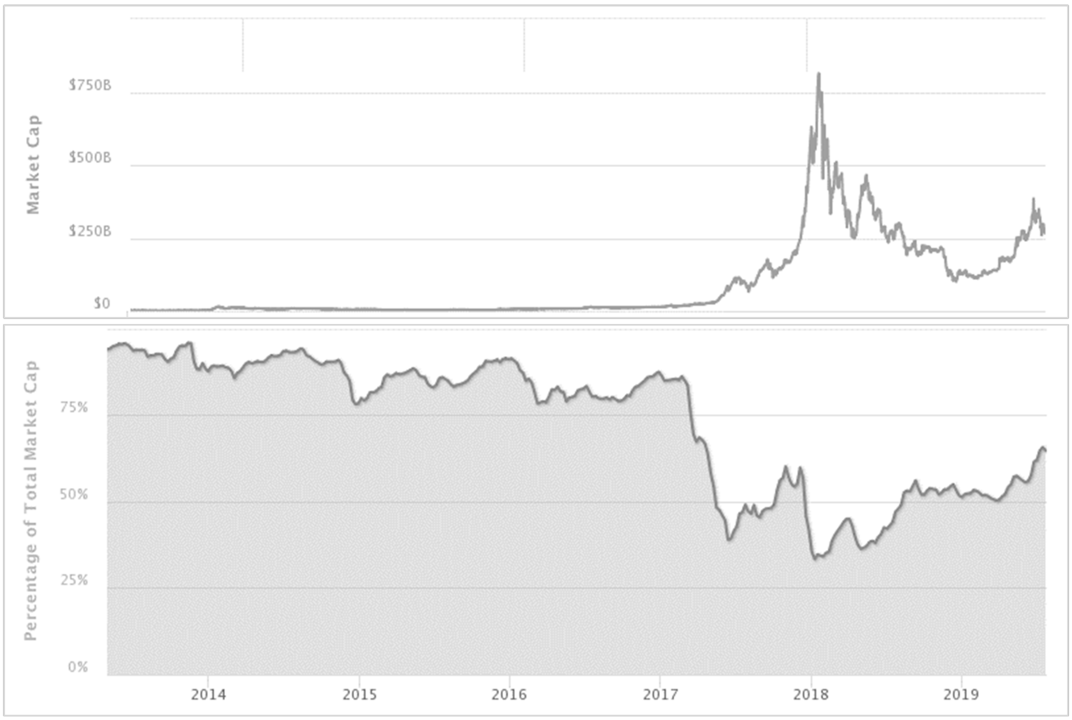
- Transaction fee: A key metric expressed in a sovereign currency that reveals the cost for transacting within the blockchain. Effectively, compares which blockchain is cheaper. Today, in most blockchain's the average transaction cost is close to USD 0.005.

- Market capitalization (market cap) or Network Value (NV): It is the product of price and circulating supply. Historically, market cap (capitalization) denotes the total market value of a publicly traded firm and equals the share price times the number of shares outstanding. Note that this financial term and not a monetary one such as monetary base is widely used in cryptocurrency language because the amount of digital assets (units) in circulation is always and precisely known. Cryptocurrencies are an unprecedented asset case for that they incorporate financial characteristics from both securities and currencies.

### 5.3.5 Bitcoin (declining) dominance and (increasing) prominence

Bitcoin is the first and remains the most popular case among cryptocurrencies. This popularity is measured by the market capitalization, that is the product of price per one unit of cryptocurrency and the supply of available units in circulation. While in currencies the monetary base (the supply) can only be estimated, in cryptocurrencies this number of how many units have been issued is always known in precise and resemble to how stocks' market cap index. Very interestingly, scholars have shrewdly embraced *networks effects* literature to relate substitution effect and reinforcement effect with Bitcoin demand for store of value and medium of exchange use respectively. In fact, Gandal & Halaburda (2014), anticipate that convergence (reinforcement effect) towards one dominant-player in (intra)competition within cryptocurrencies, thus Bitcoin is most likely. However, empirical data suggest that cryptocurrency competition within the ecosystem features also substitution effects for that as Bitcoin market value surge so do the rest of cryptocurrencies. Therefore, Bitcoin maintains a prominent rather dominant role in the market. In the next figure, Bitcoin market cap (which follows the same path as its market price since supply is pre-determined) is combined with Bitcoin market share or Bitcoin dominance-index as commonly said. It is self-evident that Bitcoin and cryptocurrency ecosystem as a whole increased their value from 2017 onward as soon competition entered and Bitcoin's share started to plunge. Bitcoin's dominance from 100% back in early 2009 has now fallen to approximately 50%.

Exhibit 5.4: Bitcoin market capitalization (top) & market share (bottom) for the period 2013-2019




*Data Source: coinmarketcap, 2017-2019*

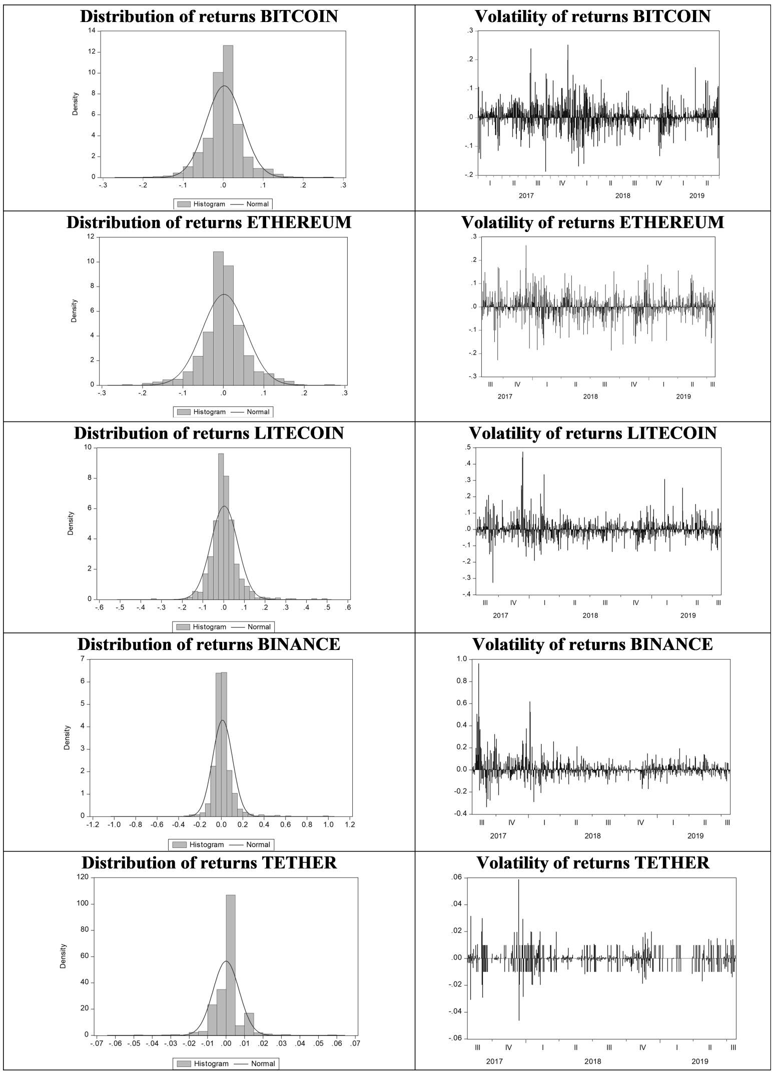
## 5.4 Investment analysis

This empirical analysis uses a representative sample and provide evidence of the general trading characteristics of these assets. In the literature, still there is no consensus on whether cryptocurrencies constitute an individual asset class mainly due to the heterogenous characteristics among cryptocurrencies. Dataset used was retrieved from coinmarketcap. This website collects data from several exchanges and calculates daily weighted averages for prices and trading volumes.

### 5.4.1 Risk-return profiles

The selected time window for this analysis is from 26th July 2017 to 26th July 2019. Thus, a complete two-year period when all following assets were traded. The five selected assets namely Bitcoin, Ethereum, Litecoin, BinanceCoin, USDTether represent the market leader of each asset class namely Bitcon, dAppcoins (Altchains), Altcoins, Utilitycoins (Tokens), Stablecoins respectively as per July 2019. In the next figure, distribution and volatility are illustrated.

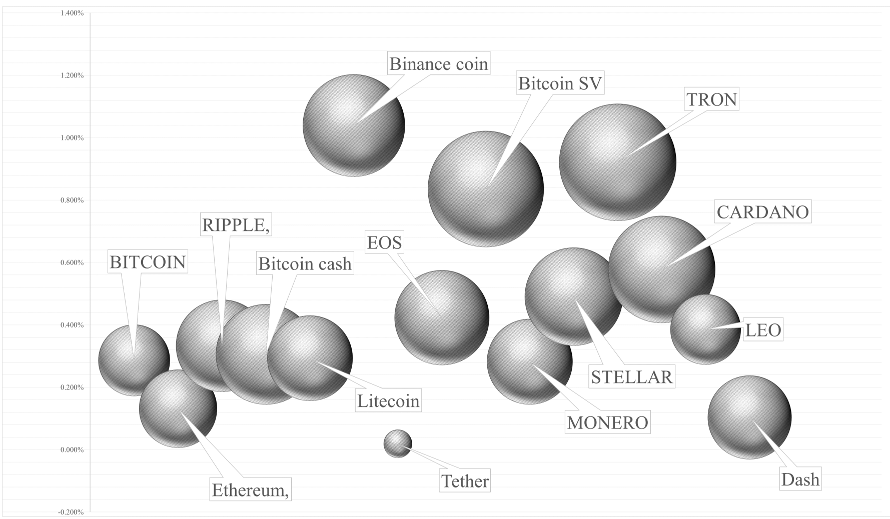
Exhibit 5.5: Daily returns 2017-2019 of selected market leaders




It is observed that the distribution of daily returns of all assets look leptokurtic and Utilitycoin exhibit the highest degree of kurtosis and standard deviation. As a result, the distribution of the Utilitycoin is right-skewed. This is reasonable as such cryptocurrencies are the closest to resemble equities. Average daily returns are close to zero within the range (0,1%-0,3%) while Altcoin exhibit the highest. As expected, Stablecoin return is zero, but price is not always 1 USD as it is originally pegged probably due to market inefficiencies that are quickly restored. Yet, the price range Stablecoin is the narrowest as anticipated.

In appendix C, calculations for the top15 cryptocurrencies from a dataset of 9.714 observations in total of daily-close returns the average mean and standard deviation for the two-year period as well as the Sharpe ratio (given by the fraction of return of asset i over standard deviation of asset i) assuming that risk free return is equal to zero are cited. Utilitycoins high mean returns are accompanied with high risk as anticipated. In contrast, Stablecoin's zero return is accompanied with a minor variation as trading opportunities raised. Notice, however, that Bitcoin's daily return was less volatile compared with other Altcoins and Ethereum for the period examined. But, the latter had also lower daily return. Altcoin (Litecoin) has a daily return close to Bitcoin's but exhibit higher risk. The results are depicted in the next figure where on the y axis is the average daily return for the period examined and the bubble specify the volatility of return.

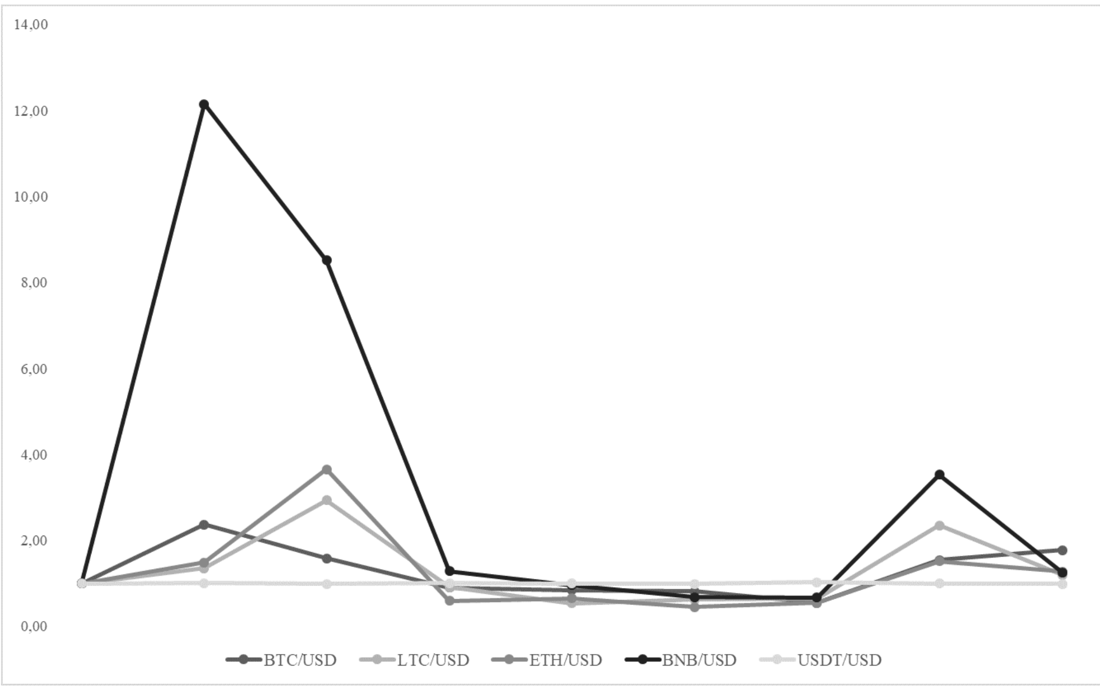
Exhibit 5.6: Relative comparison by risk-return indicators



### 5.4.2 Competition within the cryptocurrency market

This section is interested in understanding the relative movements within this market on the basis of the classification this chapter offered in advance. In appendix C, the relevant table shows the correlation coefficient for the five asset class leaders against a common sovereign currency, that is the US Dollar. As expected, all cryptocurrencies move to the same direction for that they are positive correlate with the exception of Tether. This happens because this stablecoins follows the movement of an asset outside the cryptocurrency market, that is the US Dollar. Bitcoin is in strong relation with its altcoin (Litecoin) while the strongest positive correlation exhibit Ethereum with Litecoin (0,90) and the weakest Binancecoin and Ethereum (zero). This empirical analysis divides in quarters the two-year period (2017-2019) under examination. In appendix C, the relevant table shows the figures for each pair whereas figure the next figure graphically presents the outcome.

Exhibit 5.7: Selected crypto-currencies price evolution against USD (2017-2019)

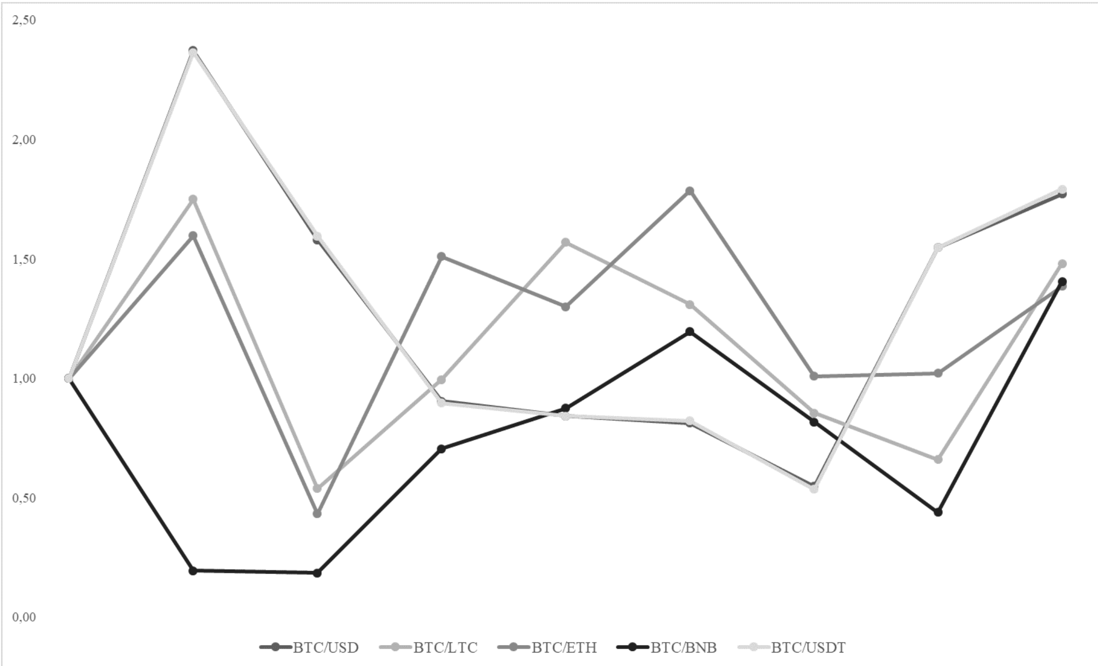



All figures are normalized to the unit at the beginning. The movement of the utilitycoin (Binanceoin) bears resemblance to a security. Notice the hype in the first quarter which happens just after its initial coin offering in 2017. The initial great trading interest in the utilitycoin then smooths as Bitcoin ends up in the period examined (July

2019) with the higher appreciation compared with the previous quarter (April 2019). For the whole period examined, Binancecoin experienced extreme movements as well as the highest appreciation in percentage terms (from USD 0,11 to 27,89) followed by Bitcoin (250%), Litecoin (116%) but Ethereum's was only 1%. Stablecoin's price change was of course 0%.

Next, the figure that follows brings an alternative perspective to the above considerations and appendix C presents the relevant results.

Exhibit 5.8: Selected crypto-currencies price evolution against BTC (2017-2019)




Under this consideration, the figure shows how the other cryptocurrencies moved in relation to the market leader (Bitcoin), again divided in quarters throughout the two-year period examined. It is self-evident that all pairs ended up higher, thus Bitcoin strengthens its dominant value. Nonetheless, quarterly analysis suggests that Bitcoin had moments of decline in relative value as indicated by the lines below the unit level. In more detail, in the end of the second quarter (January 2018) all cryptocurrencies outperform Bitcoin which bounces back later on.

### 5.4.3 Competition across traditional and other alternative investments

The study of cryptocurrencies as assets sets forth the obvious question what kind of assets are they? An interesting approach is to take the market leader (Bitcoin) and compare it to traditional and alternative investment assets. In the first place, cryptocurrencies have been inquired whether the fit in the following institutional forms namely banks, equities, commodities and cash.

- Are they bank deposits? Today, only Bitcoin value stands at more than 20 times the whole banking sector of an EU country (Greece).
- Are they low cost wealth transporters equities? Today, only Bitcoin value stands at 20 times the market value of one of leading money transfer firms worldwide (The Western Union Company).
- Are they digital-financial commodities? Today, Gold value stands at 2 times the value of Bitcoin (assuming 5.482 billion ounces of gold in the entire world according to Reuters).
- Are they cash controlled by central banks? Today, Bitcoin value stands at 20 times the whole monetary base (M0) of an EU country (Denmark). Note that the monetary base of the biggest economy worldwide is USD 3,8 trillion (USA).

Ankenbrand & Bieri (2018) compare the aggregate cryptocurrency market and established asset classes (using proxy indexes) for the period 2013-2018. As anticipated, cryptocurrencies' index average return is 13 times higher and standard deviation 8 times higher compared with stocks but correlation is significantly poor.

Comparison of Bitcoin with traditional and alternative investments is shown in the next table for a wider period of 5 years. Bitcoin's extreme volatility and negative daily return on average may be attributed to a newly established market as selection of data window is important.

## 5.5 Cryptocurrencies in modern portfolio theory and practice

In the early cryptocurrency years, investing in cryptocurrencies was characterized by a single and quite straight-forward strategy; *put money in Bitcoin and wait.* But, as

Exhibit 5.9: Table of descriptive statistics between Bitcoin and selected traditional investments and alternative investments rate of return performance (2014-2019)

| | Cryptocurrency BTC/USD | sovereign currency Danish Korona/USD | Commodity Gold/USD | Equity Western Union |
|---|---|---|---|---|
| Mean | -27,31% | 0,02% | 0,01% | 0,02% |
| Standard Error | 0,0073 | 0,0001 | 0,0348% | 0,0368% |
| Median | -8,068% | 0,007% | -0,0327% | 0,0000% |
| Mode | -75,497% | 0,000% | 0,0000% | 0,0000% |
| Standard Deviation | 0,3105 | 0,0052 | 0,012672168 | 0,013073719 |
| Sample Variance | 0,096436 | 0,000002664 | 0,000160584 | 0,000170922 |
| Kurtosis | -1,5352 | 2,5769 | 5,796293739 | 2,563527837 |
| Skewness | -0,3856 | -0,0933 | 0,352639159 | 0,022577608 |
| Range | 1,067670869 | 0,053356239 | 0,143748713 | 0,132804116 |
| Minimum daily return | -81,52% | -2,95% | -6,99% | -6,87% |
| Maximum daily return | 25,25% | 2,38% | 7,38% | 6,41% |
| Number of observations | 1825 | 1367 | 1328 | 1260 |
| Confidence Level(95,0%) | 0,014256881 | 0,000273896 | 0,000682176 | 0,00072257 |

the market started to grow in the advent of other cryptocurrencies that showed strong market capitalization and volume, then new strategies arise. As a result, researchers started to construct Markowitz mean-variance models derived from the classic finance literature applied to traditional and alternative investments as well in an attempt to examine portfolio diversification issues.

Recall the expected return:

$$E(R_p) = \Sigma_i w_i E(R_i)$$

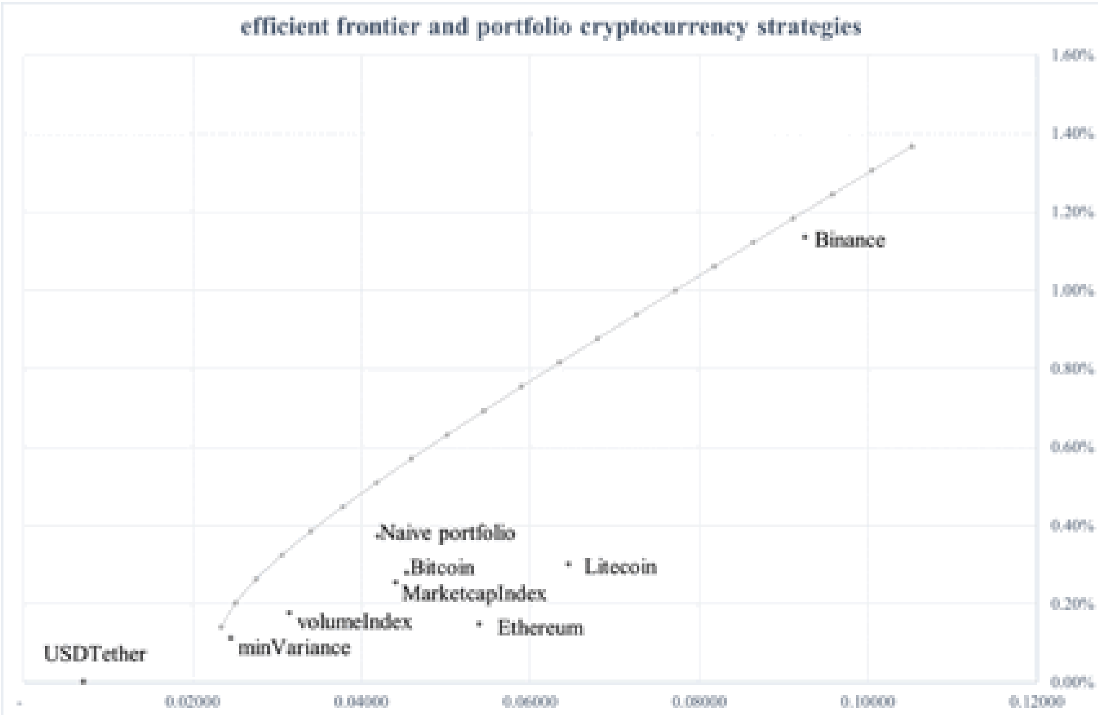
And, the portfolio return variance:

$$\sigma_p^2 = \Sigma_i w_i^2 \sigma_i^2 + \Sigma_i \Sigma_j w_i w_j \sigma_i \sigma_j$$

where (i) is the asset, ($w_i$) the weight of each asset in the portfolio, ($\sigma_{ij}$) is the standard deviation of asset i and ($\rho_{ij}$) is the correlation coefficient of assets i and j. Under this frame, Brauneis & Mestel (2019) test for various portfolios and their out-of-sample analysis support that blending cryptocurrencies yield better combinations of mean-variance. Liu (2019) use less number of cryptocurrencies, yet end up to the same conclusion. Later on, research shifted attention to investment strategies mixing traditional and alternative investment assets with cryptocurrencies. Baumöhl (2019) examine connections with the Foreign Exchange market and Kurka (2019) extend to include other traditional asset classes such as commodities and securities. In the same spirit, though focusing only on the market leader (Bitcoin), Guesmi et al. (2019) show that hedging strategies involving Bitcoin considerably reduce portfolio's risk.

The next plot visualizes the location of the five proxy cryptocurrencies selected in this investment analysis and in addition the realization of portfolio strategies across cryptocurrencies.

Exhibit 5.10: Efficient frontier and portfolio strategies across cryptocurrencies




This approach illustrates the mean-variance framework four portfolios strategies including all these five cryptocurrencies. In specific, (a) min Variance was constructed by optimizing (minimizing) portfolio's variance, (b) MarketcapIndex computes weights based on each cryptocurrency market cap, (c) Volume Index follows the same logic, though taking into account volume and (d) stands for a naive portfolio (1/N) where N=5 the number of assets. Efficient frontier features the combination of the optimal portfolio assuming short-selling and a mix of Bitcoin and the Stablecoin. In appendix C, the relevant table presents the calculations.

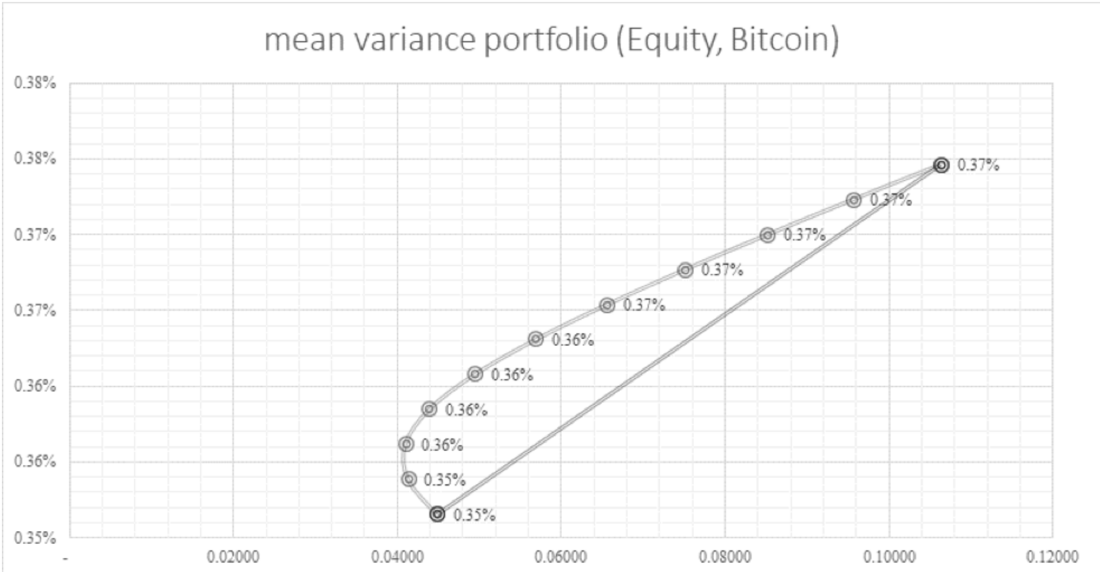
In the next plots, portfolio diversification possibilities are pointed out in combinations of the market leader (Bitcoin) with the three proxies taken above with regards to the three traditional and alternative investment categories (data from Investing.com).

1. equities taken as proxy Western Union Company,
2. commodity markets taken as proxy Gold,

3. foreign exchange (ForEx) markets taken as proxy the Danish Korona.

The diversification result for the first case (equity markets and cryptocurrency markets) is evident in the next figure.

Exhibit 5.11: Mean-variance portfolio including equity and Bitcoin




The diversification result for the second case (commodity markets and cryptocurrency markets) and for the third case (foreign exchange markets and cryptocurrency markets) are evident in the next figures that follow.

Exhibit 5.12: Mean-variance portfolio including commodity and Bitcoin

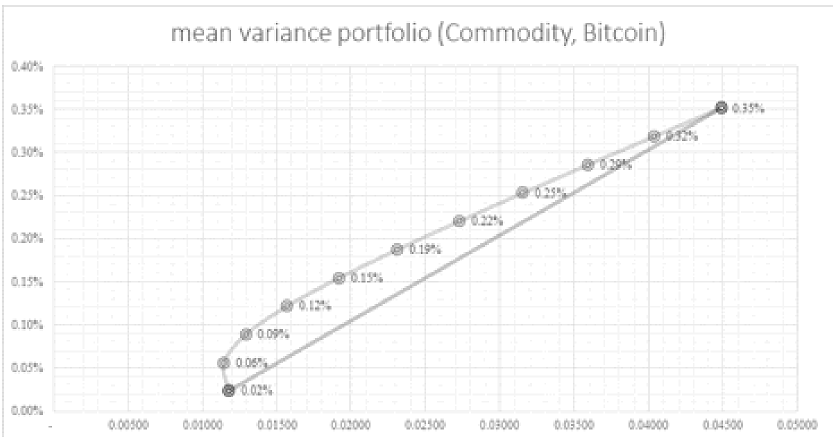
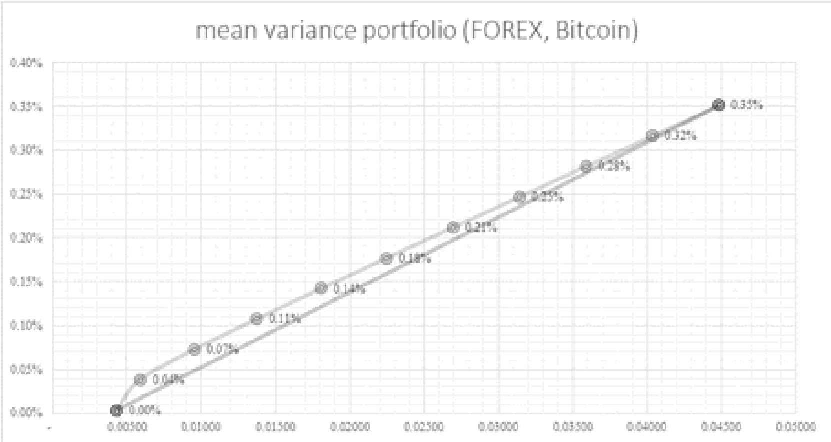


Exhibit 5.13: Mean-variance portfolio including ForEx and Bitcoin




## 5.5.1 Pricing cryptocurrencies

Standardized valuation models have generated debate, such as over how best to price cryptocurrencies. It is most certain that the lack of widely acceptable valuation methodologies has been a reason why investment interest in cryptocurrencies remains in the sidelines with no room for adoption from professionals in the asset management industry. Is it a currency, commodity, security, derivative or combination? Cryptocurrencies operate outside conventional concepts of both traditional and alternative investment assets. It is self-evident that cryptocurrencies and commodities are not alike since the former have no alternative use, thus have no intrinsic value. Moreover, cryptocurrencies and equity securities are not alike since the former do not formally enter into the equity structure of the firm. Similarly, cryptocurrencies and sovereign currencies are not alike since the former are not associated (a) with legal tender, neither (b) with term structure of interest rates nor (c) with national trade imbalances, thus have no fundamentals. On account of that, traditional valuation models fall short. In the empirical price formulation literature on cryptocurrencies, until now studies have mostly expressed interest in Bitcoin. Methodology and findings can be grouped in three categories. First, (a) market forces of demand and supply (Kristoufek, 2013; Ciaian et al., 2016; Tasca & de Roure, 2014) where currency models are mostly applied to reject the hypothesis of medium of exchange motive. Second, implied motives (Brito & Castillo, 2013; Yermack, 2013; Bouoiyour et al., 2014; Glaser et al., 2014; Garcia et al., 2014; Kristoufek, 2015) which rely on revealed preferences drawn from search queries, social media big data, public information, attention of news that conclude in support of the speculation motive. Third, (c) macro-finance global financial markets (van Wijk, 2013; Ciaian et al., 2016; Sovbetov,

2018) which relate prices with indices, commodities, currency exchange rates, economic indicators and other cryptocurrencies etc., yet inferences are inconclusive. In conclusion, theory and practice have examined the following pricing methodologies:

- Fundamental analysis: This refers to approaches to identify and model fundamental factors, if any of cryptocurrencies within the traditional finance valuation literature (Zhang et al., 2018).

- Currency models. Initially, Bitcoin was deemed as a currency, thus the initial belief was that it cannot be valued but rather priced by the interaction of supply/demand. Models that have been employed in literature include Quantity Theory of Money, Gold Standard, Purchasing Power Parity and neoclassical models with money in the utility function. All studies have strongly rejected the transaction motive hypothesis.

- Commodity models. Then, Bitcoin's high volatility was thought to resemble a commodity than a typical currency. Again, this has been proven problematic for that there is no actual alternative use of this asset like commodities that possess an intrinsic value. Though, in some cases the return may be perceived as a convenience yield.

- Securities models: Later on, the equity side of these asset was suggested. Opponents argued that they are not securities for that they do not generate money flows. It is true that, cryptocurrencies seem to trade more like perpetual bonds than stocks. As said, Steem Power cryptocurrencies have some features of equity. An interesting argument is that as cryptocurrencies' markets lack efficiency and prices cannot be easily attributed to fundamentals, in contrast technical strategies may become more effective (El Alaoui et al., 2018).

- Technical analysis: This type of valuation analysis focuses on past trading activity. Arguably, it is the most widely used method in cryptocurrency investment practice since fundamentals (news such as halving the amount of new supply) are rare events in these alternative assets.

- Algorithmic trading and strategies based on past statistical performance have been openly regarded as profitable for that they identify and restore trading opportunities. Cryptocurrencies like Bitcoin that are characterized by absence of news from the supply-side since they follow a pre-determined path may identify repeatable patterns of price movements and signals. This is because all these are exclusively attributed to demand factors like sentiment and arguably past behavior.

- Relative valuation analysis based on trading metrics as earlier explained. Comparing these metrics for one cryptocurrency against a similar cryptocurrency of other asset traded in the real economy produces relative measures to identify possible misvaluations.

## 5.6 Concluding remarks

This chapter delved into the newly emerged cryptocurrency market. In effect, aimed at showcasing cryptocurrencies as part of the alternative finance and investment firmament. By now, the reader should have understood that while cryptocurrencies resemble to traditional investments such as cash and securities, should be conceived as alternative investments assets due to the peer-to-peer primary (initial offerings at issuance) and secondary (for exchanging and redeeming) markets.

# Chapter 6

# On the Weak Form Efficiency within and across cryptocurrency market indexes

The study of peer groups and indexes as the cryptocurrency market grows is important for matching investors' tastes and preferences. We use daily data frequency of 57 cryptocurrencies throughout their entire trading history, aiming to draw inferences about the weak form efficiency hypothesis, yet conditional on the varieties of crypto-asset classes. Against this background, we investigate stylized facts traditionally found in daily returns, by employing tests for the presence of effects namely symmetric time-varying, risk premium, leverage and calendar. The findings of peer-group effects show the competition across these composite market cap indexes as well as within allowing to compare cryptocurrencies' trading performance more evenly.

## 6.1 Introduction

The asset price of cryptocurrencies, that is their exchange rate in terms of another currency either traditional (such as the US dollar or the Euro) or alternative (other cryptocurrencies) is determined in numerous private digital exchanges. Therefore, the cryptocurrency alternative market is attached to the traditional foreign exchange market which is "in operation twenty-four hours a day, seven days a week, and is the closest analogue to the concept of a continuous time global marketplace" (Bollerslev & Domowitz, 1993). Without a doubt, the declining Bitcoin dominance ratio as measured by the ratio of Bitcoin market capitalization over total market capitalization has high- lighted the fact that the cryptocurrency market matures due to the constant diffusion of plethora new alternative assets. But, it comes as a natural consequence to ask whether all these alternative assets are similar in terms of trading behavior and performance. Closer look at the definitions and properties of cryptocurrencies allows us to identify important differences. Therefore, just like in security and commodity markets, cryptocurrency alternative markets call for proper investigation both within and across homogeneous asset-classes. This can be useful for investors with different tastes in their allocation decision among assets and indexes. In this work, we examine the dominant market player (Bitcoin) as a distinct asset class compared to other cryptocurrency asset classes as we draw a sample in order to construct different indexes and market cap portfolios. These categories would be the next:

1. **Bitcoin**, the market pioneer and leader stands for a stand-alone index.

2. **Altcoins**, thus alternative to the Bitcoin blueprint for that they are openly regarded as clones only to feature different parameter values in the protocol i.e. different block time for clearing transactions, supply function, and issuance scheme.

3. **Altchains**, thus alternative type of the Bitcoin blockchain blueprint. These assets create more ecosystems for that their main role is becoming a platform for the development and execution of various smart contract (called dApps) on top of their network.

4. **Algorithmic Stable** follow crawling pegs exchange rate arrangements as they fluctuate over accepted small bands. Their goal it to peg the decentralized cryptocurrency (called Algorithmic Stable) to another anchor (usually traditional currency at parity) through stability mechanisms governed by holders of a centralized cryptocurrency (called Smart Token, see below for more). Their reserves are either over-collaterized (allowing trading on margin via Collaterized Debt Position derivatives) or non-collaterized.

5. **Stable Tokens** follow the currency board exchange rate arrangement and are privately (by firms) issued following the acceptance of another anchor (traditional currency or commodities) which is kept as collateral reserve.

6. **Smart Tokens**, are not related to products or services in the real economy and either act as governors for algorithmic stable cryptocurrencies or simply as tokens that allow the participation in a virtual applications.

7. **Utility Tokens** are privately issued (by firms) as pre-payments for the payment of a particular product or service in the real economy (offered by the originator).

While many empirical studies have been conducted to delve into various aspects of risk-return relationship of cryptcurrencies, this topic as far from being exhausted as a research area. Lately, it has been identified the need to construct benchmarks and indexes (Trimborn & Härdle, 2018) so as to better identify over and under performance of cryptocurrency asset markets which at the beginning of 2018 peaked at USD 700 bil. Evidence of market anomalies in assets and constructed indexes hint at possible return predictability which is inconsistent with the efficient market hypothesis. As the cryptocurrency matures in size and value the need to classify these assets in indexes that follow common patterns alike traditional regulated (stock and foreign exchange) markets will become greater. This paper is motivated by this research agenda. The remaining paper is organized as follows. Section 2 reviews literature, section 3 cites preliminary statistics and explains the methodology while sections 4,5 and 6 provide the estimation results. At the end, section 7 concludes and extends.

## 6.2 Literature

The Efficient market hypothesis [EMH] postulates that under rational expectation, perfect and completer markets agents instantly update their expectations appropriately as new information comes in and therefore the asset prices already reflect all known private and public information. The support of this hypothesis is studied more closely with regards to three traits namely (i) returns are not predictable, (ii) returns do not exhibit non-diversifiable risk, thus the risk should be reflected in the price and (iii) absence of persistence in returns, thus analysis of past and current information do not offer much to traders. The fundamental concepts of efficient market hypothesis were first systematically studied by Samuelson (1965), then formulated to their current framework that distinguishes between *weak-form efficiency*, *semi-weak form efficiency* and *strong form efficiency* by Malkiel & Fama (1970). Finally, the hypothesis was revisited by E. F. Fama (1991) who methodologically relates the three form with *predictability tests*, *event studies* and *private information test* respectively.

From the empirical investigation standpoint of view, the Efficient Market Hypothesis is greatly evaluated under two frameworks. The first examines the assets' time-series behavior over time either in relation to the announcement of information or standalone, thus looking at their own trading path. The goal is to identify patterns of non-randomness in returns. The second strives to identify empirical (market) anomalies that violate the bold assumption that no-one can beat the market. On the research question of efficient market hypothesis in cryptocurrency markets, the findings of current literature are inconclusive on account of different modeling techniques and periods selected. Caporale et al. (2018) identify persistence (positive correlation between past and future values) of changing degree over time that can allow trading strategies to gain abnormal profits. Kaiser (2019) examines seasonality effects in key trading variables (volume, spread, volatility) for ten cryptocurrencies to conclude that the weak-form market efficiency cannot be rejected. An event study for macroeconomics news is found in Al-Khazali et al. (2018) while the size-effect is explored in Shen et al. (2019) who use a three-factor pricing model.

## 6.3 Preliminaries

This section is meant to provide a concise overview of the methodology employed and thee main statistical features of the assets in question prior to the main analysis by reporting graphs and figures.

### 6.3.1 Data & descriptive statistics

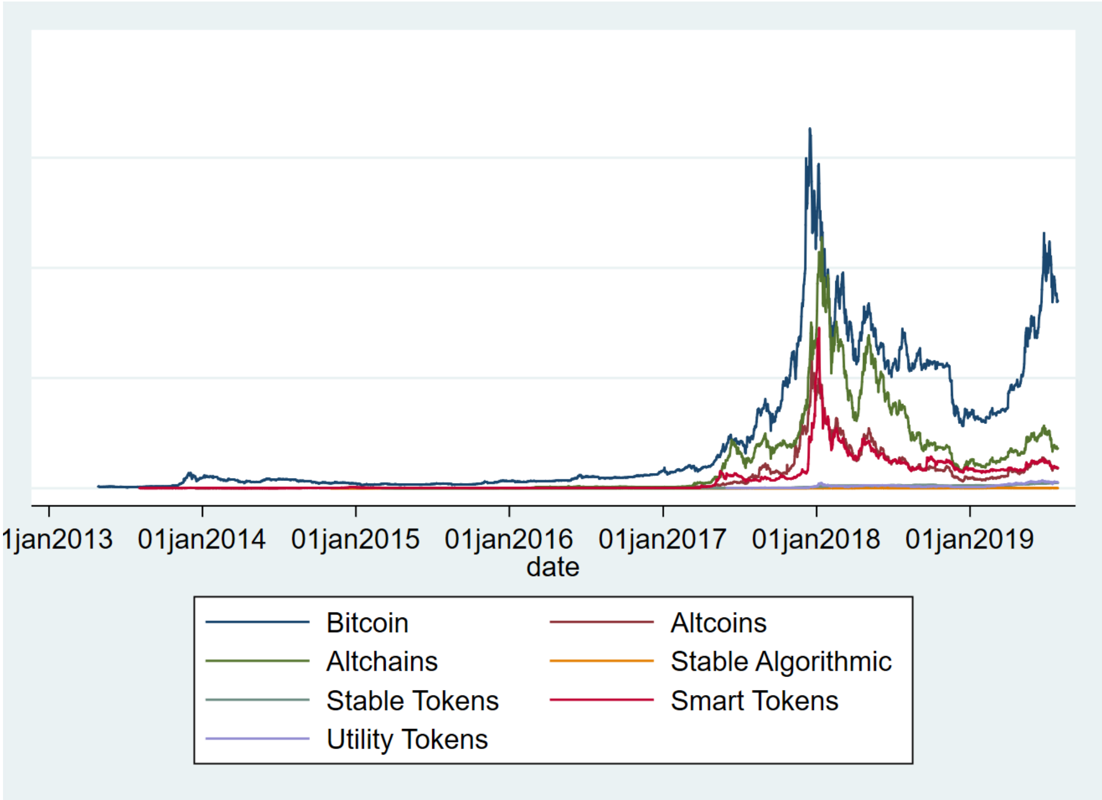
The data used are for the period from April 28, 2013 until July 29, 2019, thus account for almost the entire cryptocurrency market trading history which had started a few three years ago, yet with considerably low volume and capitalization.[1] In the next figure, the lines display the market capitalization (market cap indexes at levels) evolution for the selected sample of 57 cryptocurrencies segregated into groups. The market cap indexes is the summation of individual cryptocurrency market cap corresponding to each asset class. Hence, the market cap index of daily returns stands for a portfolio which accounts for the individual market cap weight of each asset.[2]

The figure shows periods of excessive turbulence and tranquility which possibly implies the existence of volatility clustering. Based on the selected sample of the most active cryptocurrencies, Bitcoin trading history is the longest followed by Smart Tokens which were first launched in August 2013 and Altcoins in December of the same year. In November 2014, the trading history of Algorithmic Stable commences and in May 2015 the one of Stable Tokens. Around that time, in April 2015 Altchains are issued. Last,

[1]The data were obtained from coinmarketcap.com

[2]Appendix D presents the whole sample and details of classification.

Exhibit 6.1: Market capitalization 2013-2019 by cryptocurrency market cap index




but not least, since June 2017 Utility Tokens have come to existence. Some asset classes tend to share common paths as a whole (Bitcoin, Altchains, Smart Tokens) primarily driven by Bitcoin's overall performance, yet the rest having less market capitalization seem to be less affected possibly highlighting the diverse rationale and growth of each asset class. The figure also shows that in the first months of 2019 the Bitcoin dominance is strengthen at expense of the other classes while in earlier years this relationship was more tight.

Following, we computed the logarithmic daily return and assumed continuous rate of return. Thus, (k=1 for the daily change)

$$r_t(k) = ln\frac{V_t}{V_{t-k}}$$

The letter V stands for market cap for indexes and prices for assets. An important note. In this work, the daily return on an composite index represents the daily change in market capitalization. On the other hand, the daily return on individual cryptocurrency assets within these composite indexes are calculated on the basis of the daily return on the price. This means that the return on the Bitcoin Market cap index (based on market capitalization) does not coincide with the return on the Bitcoin asset (based on prices). The rationale is to attempt the construction of composite indexes that could possible lead to inferences. In this work, market capitalization addresses both the change in prices and the change in (money) supply. We used the closing value in the nominator and the opening value in the denominator to address possible discrepancies with previous date closing values as cryptocurrencies are trading every second over multiple exchanges and the notion of daily closing prices is not similar to equities.

The next histograms offer a first idea about the dispersion of daily rate of return for each market cap index. Discussion on return on assets (thus, daily change in prices) will accompany this analysis in the next sections.

Exhibit 6.2: Daily rate of returns of market cap indexes 2013-2019 Panel A

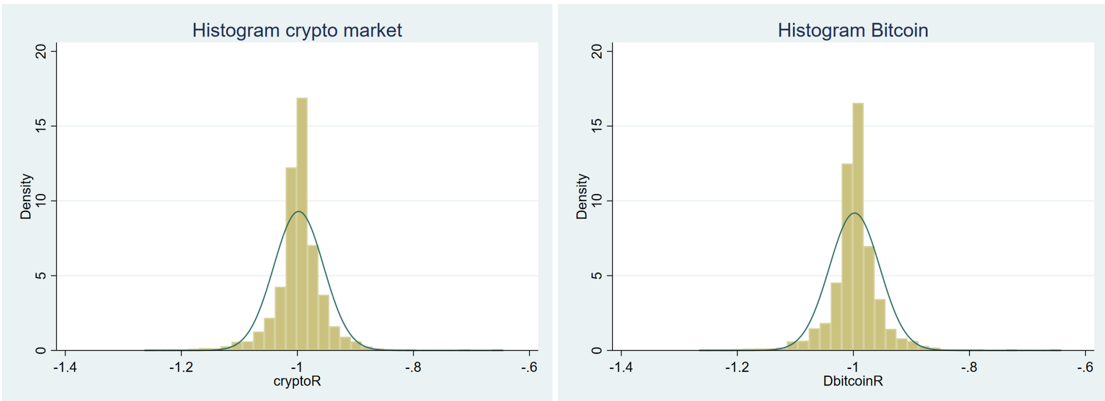



Exhibit 6.3: Daily rate of returns of market cap indexes 2013-2019 Panel B

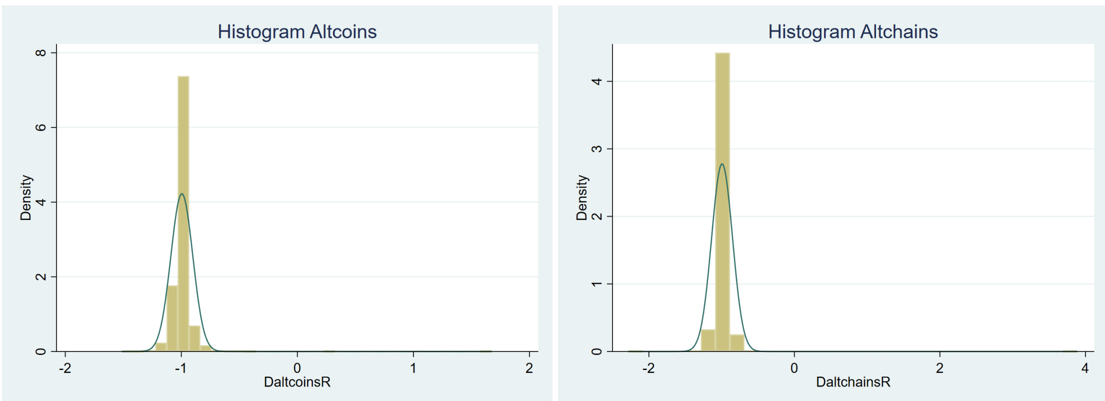


Exhibit 6.4: Daily rate of returns of market cap indexes 2013-2019 Panel C

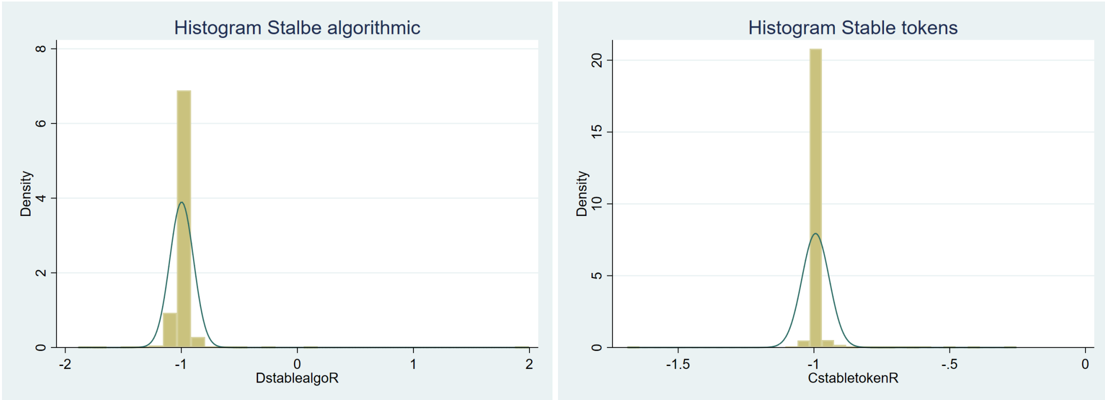
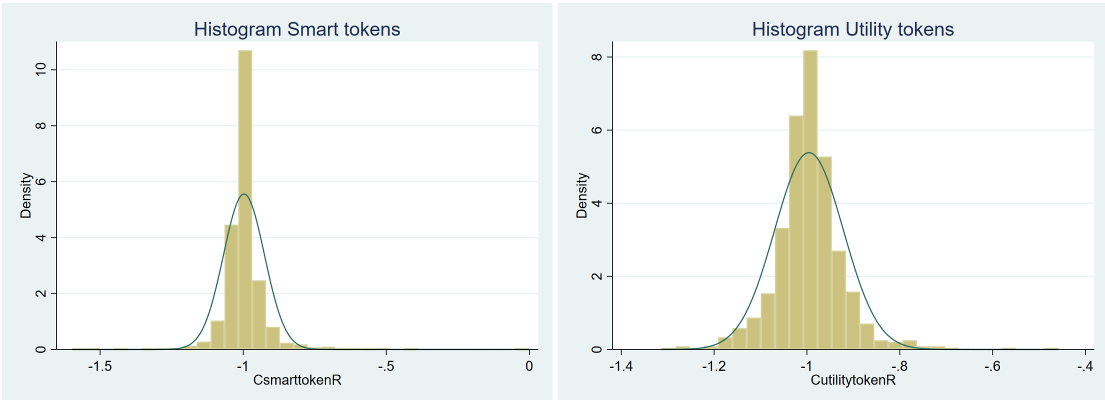



Exhibit 6.5: Daily rate of returns of market cap indexes 2013-2019 Panel D




The data indicate that the higher daily return on average is offered by Smart Tokens while the highest range (max, min) as well highest dispersion of returns from its average are yielded by Stable Algorithmic due to failure of some assets in this class to achieve stability in a decentralized fashion. The distributions are mostly skewed to the right, thus have values spread out in the negative direction on the number line (the mean is to the left of the peak and skewness for the whole market cap is 3 on average. Also, the distribution are mostly leptokurtic (fat-tailed) since kurtosis is significantly above 3. Therefore, this is in line with the first stylized fact. Overall, the table shows evidence of unconditional non-normal distribution. Looking at theses findings, we formally tested the null hypothesis of normality using a variation of the Bera-Jarque (BJ) test.[3] The

[3]In contrast to the traditional one, this test corrects for the small sample bias of the BJ test by using a bootstrapping procedure. The test implements the procedure described in D'agostino et al. (1990).

results strongly reject the hypothesis with the exception of Unus Sed Leo [LEO] belonging to the Smart Tokens genre where the hypothesis is only rejected at 10% significance level. The relevant results are omitted.

In order to grasp the riskiness of each index we introduced the concept of "Value at Risk" (VaR) using the historical method[4] by arranging returns in ascending order and calculating the correspondent percentiles. According to the results, we infer that with 95% confidence worst daily loss is expected not to exceed 9,65%. The less risky asset is Stable Token as expected due to its centralized nature (backed by a firm).[5] These figures underscore crypto-market cap extreme volatility which is should be considered high among trading assets worldwide. Moreover, we introduced the concept of downside risk which is one-sided test for unexpected decline in value. We calculated the standard deviation of the observations that only fall short of the asset's average and we see that Bitcoin's downside risk is higher in this case. A summary of preliminary statistics by asset class is provided below. In the first column, the letter D stands for Decentralized cryptocurrency and the letter C for Centralized cryptocurrency. The values of arithmetic mean, maximum, minimum, standard deviation, kurtosis, skewness, downside and VaR correspond to the average of each group-index. The values in the second row show the average of each metric from the 57 assets (initial data), thus not from the 7 group-indexes (constructed).

Exhibit 6.6: Table of summary statistics

| Name of asset class | Number of assets | Number of observations | Arithmetic mean | Max | Min | Standard deviation | kurtosis | skewness | downside risk | VaR (5%) |
|---|---|---|---|---|---|---|---|---|---|---|
| | **57** | **49,349** | **0.0052** | **0.9944** | **-0.3506** | **0.0863** | **49.9456** | **3.2999** | **0.0295** | **-0.0965** |
| ***D Bitcoin*** | 1 | 2,284 | 0.003 | 0.417 | -0.229 | 0.043 | 9.274 | 0.465 | 0.033 | -0.064 |
| ***D Altcoins*** | 12 | 13,718 | 0.004 | 1.223 | -0.463 | 0.098 | 48.273 | 3.539 | 0.038 | -0.112 |
| ***D Altchains*** | 19 | 14,651 | 0.005 | 1.026 | -0.371 | 0.094 | 51.544 | 3.386 | 0.033 | -0.110 |
| ***D Stable Algorithmic*** | 3 | 3,389 | 0.004 | 2.828 | -0.582 | 0.114 | 278.268 | 12.858 | 0.041 | -0.062 |
| ***C Stable Token*** | 5 | 3,164 | 0.000 | 0.087 | -0.065 | 0.013 | 13.418 | 0.376 | 0.006 | -0.020 |
| ***C Utility Token*** | 5 | 2,957 | 0.006 | 0.886 | -0.251 | 0.091 | 24.127 | 2.894 | 0.023 | -0.106 |
| ***C Smart Token*** | 12 | 9,186 | 0.008 | 0.729 | -0.319 | 0.088 | 21.374 | 2.159 | 0.025 | -0.099 |

[4]There are three widely accepted methodologies in literature i.e. non-parametric (including the historical method), parametric and semi-parametric. See Abad et al. (2014)

[5]Formulas:

$$VaR = \frac{1}{rank(N)} \times \sum_{1}^{N} r$$

where Rank(N) = (1-quantile)*number of observations and r is the daily return (after the daily returns have been sorted in ascending order).

### 6.3.2 Notations & methodological framework

We use the following notations to facilitate the understanding of the theoretical background applied to the empirical examination that follows:

- The (unconditional) expectation of the t-th return is $\mu$(t) = E($X_t$)
- The (conditional) expectation of the t-th return is $\mu(t) = E[X_t|X_0, X_1, ...X_{t-1}]$
- The covariance between the returns at times s and t is cov(s,t) = E[X(s) - $\mu$(s)][X(t) - m(t)]
- The variance of the t-th return is var(t) = cov(t,t)
- The correlation between the returns at times s and t is $\rho(s,t) = \frac{cov(s,t)}{\sqrt{var(s)var(t)}}$

This work studies market efficiency of cryptocurrencies for a representative sample which corresponds to all cryptocurrency asset classes. On the whole we define the next categories namely (a) strict white noise (SWN), (b) martingale difference sequence (MDS), (c) weak white noise (WWN) and (d) random walk (RW) which is a non-stationary martingale sequence by definition whereas the first three are stationary (Fabozzi, 2009). In a strict (or also colloquially referred to as independent) white noise process, the random variables:

1. are both unconditionally and conditionally centered, thus the mean is zero for all t
2. are independent and identically distributed (i.i.d)
3. are not serially correlated
4. are strictly stationary, that is the probability distribution of the vector [X(1), ...,X(t)] is invariant across time

These properties gradually drop for the other three categories. In specific, a stationary martingale differences sequence (MDS) process allow for non interdependence with finite (heteroskedastic) variance as in the case of ARCH models introduced by (Engle, 1982). Next, weak (or simply) white noise (WWN) allow processes to have conditional means different from zero, although the conditional one remains so. Conversely, random walks (RW) are characterized processes that have unit root (non-stationary), time variant variance and some serial correlation exists. Non-stationary data, thus random walks which are an example of martingale processes are unpredictable and cannot be modeled. It would be of great interest to understand where do cryptocurrency asset classes fall into. It is in this light that we shall examine the daily returns in terms of serial correlation, independence and stationarity.

Having said that, financial data are related to some stylized facts for which we aim at drawing inferences either in support or not. These are as follows:

1. Returns are leptokurtic or heavy-tailed
2. Returns show low or zero serial correlation (but squared returns usually show significant)
3. Prices are non-stationary but returns are stationary
4. Conditional expected returns are close to zero
5. Volatility appears in clusters, thus large returns followed by large returns and viceversa

If we look more closely at these stylized facts, we find that the conditions of no serial correlation and stationarity are sufficient in characterizing the returns as white noise in support of the weak form efficient market hypothesis. Moreover, if we find that the variance is finite and constant then the returns are strict white noise. In contrast, in the event of unit root in returns, then the sequence follows random walk. Autocorrelation refers to the phenomenon of correlation between the values of a random variable at different points in time. Stationarity relates to the fact that the statistical properties of a process generating a time series do not alter over time. Stationarity comes in different forms (weak also called second-order, strong also called first-order). All the same, non-autocorrelation and stationarity are important for that are easier to model and in turn, statistically analyze with confidence relationships underlying variables over time. Put it simply, inferences can be closer to reality.

## 6.4 Random walk estimation & inferences

The most popular case for testing random walk is unit root tests.[6] Unit root tests are parametric and examine whether a variable is non-stationary or, equivalently, that it

[6] More specialized tests include Wild-bootstrapped automatic variance ratio tests and spectral shape tests as implemented by Nadarajah & Chu (2017) in investigating evidence of market efficiency of Bitcoin.

follows a random walk. Rejection of the null hypothesis of unit root results to infer that the sequence is stationary. The ADF test (Dickey & Fuller, 1979) assumes that the sequence follows an AR(k) process and add lagged difference terms of returns (the dependent variable) to the explanatory set of variables. The test involves fitting the model of the form

$$\Delta y_t = a + \beta y_{t-1} + \delta t + \zeta_1 \Delta y_{t-1} + ..... + \zeta_k \Delta y_{t-k} + \epsilon_t$$

where k is the number of lags and we use three types of linear ADF test models i.e (i) random walk where drift and trend are allowed (called trend), (ii) random walk with drift but no trend, thus $\delta$ is restricted to be zero (called drift model) and (iii) random walk with no drift and trend, thus a is also restricted to be zero (called no constant model). The nonzero drift parameter accounts for the fact that financial data usually show that mean is nonzero. The k parameter is a set of lags added to tackle possible serial correlation (examined in more detail later). The selection of the number of lags in ADF can be done on the basis of selection criteria like Aikaike information criterion (AIC), Schwarz information criterion (SIC), Hannan-Quinn criterion (HQC). We report the results of the test statistic of the daily returns on market cap indexes (aggregate of the market capitalization of cryptocurruencies grouped into asset classes) in the next table. The null hypothesis is that there is a unit root. Next to each test statistic is the acceptance at the significance level where (*) indicates at 10%, (**) at 5% and (***) at 1%.

Exhibit 6.7: Table of ADF tests for stationarity of market cap index daily return

| Models: | Levels DF test (no lags) values of test statistic | | |
|---|---|---|---|
| **Market cap index** | **Trend model** | **Drift model** | **No constant model** |
| Bitcoin Marketcap | -47.952*** | -47.963*** | -47.867** |
| Altcoins Marketcap | -44.080*** | -44.042*** | -43.952** |
| Altchains Marketcap | -48.583*** | -48.518*** | -48.428** |
| Stable Algo Marketcap | -47.191*** | -47.189*** | -47.156** |
| Stable Token Marketcap | -40.118*** | -40.117*** | -39.566** |
| Smart Token Marketcap | -43.858*** | -43.867*** | -43.816** |
| Utility Token Marketcap | -26.751*** | -26.758*** | -26.681** |
| TOTAL Crypto Marketcap | -48.532*** | -48.542*** | -48.422** |

As shown in Appendix D (Table of ADF tests for stationarity), stationarity tests were applied to all assets of the sample.[7] According to the results all returns are stationary (tested for both for no lags and higher order of lags until the coefficients turn insignificant). Prices, of course, are not stationary in accordance with this stylized fact widely encountered in financial data.

Since we have determined the randomness of the sequence in terms of stationarity we proceed to examine the nature of white noise (weak white noise or not) in the presence of this stationarity.

## 6.5 White noise estimation & inferences

White noise tests are plenty and come with different assumptions and methods. In this part, we shall examine the data with regards to serial correlation, independence and time-varying volatility. A white noise process is a serially uncorrelated stochastic process with a mean of zero and a constant and finite variance which implies that is a weak stationary process.

If we detect normal distribution (zero mean and same variance), although highly unlikely as already shown in the preliminary statistics sections then this is referred to as *Gaussian white noise process* (Fabozzi, 2009). Even though we do not formally test for Martingale Differences Sequence (MDS)[8] we can implicitly arrive to such inference for that we shall examine the presence of ARCH effects which are by definition a Martingale Differences Sequence, thus a variation of White Noise.

### 6.5.1 Tests for serial correlation

Statistically, the absence of significance in autocorrelation coefficients in returns imply that returns follow a white noise sequence, which in turn means that the market is efficient at the weak level. A first attempt to access autocorrelation is the correlogram which depicts the correlation statistics. In addition to that, we formally test for autocorrelation with the Ljung and Box portmanteau statistic for up to 3 lags.[9] This tests the

[7] In Appendix D, the relevant tables for the three variations of the stationarity test are provided. Note that the left side of the table shows the three models without lags while for the models on the right side lags have been assumed. A common way to start is with a large number of lags selected *a priori* and reduce the number of lags sequentially until the longest lag is statistically significant.

[8] Applications of Martingale Differences Sequence (MDS) tests can be found in Escanciano & Velasco (2006).

[9] Note that this test statistic Ljung & Box (1978) is a refinement of the original version submitted by Box & Pierce (1970) also called portmanteau Q-test.

overall randomness based on a pre-determined number of lags and not at each distinct lag. The null hypothesis is that no correlation exists and the test statistics is in the next form

$$Q = n(n+2)\Sigma_{k=1}^{h}\frac{\rho_k^2}{n-k}$$

From the Ljung and Box portmanteau statistic we infer that the market cap indexes suggest that only Utility tokens index is not autocorrelated while all other indexes strongly reject the null hypothesis. From the assets standpoint of view as shown in Appendix D, we use a general approach to test for 3 lags. We infer that Stable Cryptocurrencies (both Algorithmic and Tokens) are non-autocorrelated while 50% - 60% of the sampled assets in the other classes are not. For Bitcoin in particular, the first 1-4 lags reject the null hypothesis but after 4 lags autocorrelation appears.

Alternatively, we employ the Breusch and Godfrey Lagrange Multiplier (LM) test (colloquially termed the LM test) for that allow to rest for high orders or serial correlation as opposed to the Durbin and Watson test which is another similar test. This is an extension of the standard Ljung and Box (Q) test. The latter is applicable for univariate time series under the assumption of strictly exogenous regressors while the former accounts for weakly exogenous regressors. This means that it is not applicable in the presence of conditional heteroskedasticity in the error process. We will deal with time-varying volatility very shortly. The Breusch-Godfrey test first runs an auxiliary OLS model as follows:

$$\hat{u_t} = a_0 + a_1 R_{t-1} + a_2 R_{t-2} + a_3 R_{t-3} + \rho_1 \hat{u_{t-1}} + \rho_2 \hat{u_{t-2}} + \rho_3 \hat{u_{t-3}}$$

and then multiplies the number of observations (n) with the $R^2$ from the above regression. This is the LM statistic which is asymptotically distributed as $\chi^2$ with p degrees of freedom (where p is the k number of lags). The null hypothesis is that there is no serial correlation up to lag order p. We apply the test by regressing each time series on a constant and for the lags identified in the stationarity tests. So, in this case the units vector (explanatory variables) are render strictly exogenous. We observe that the results of the two tests conclude both across and within the asset classes.

A final comment. We also applied the Bartlett test wherein the null hypothesis is that data come from a white-noise process of uncorrelated random variables having a constant mean and a constant variance. Results agree with the previous. For example, for all market cap indexes the values appear outside the confidence bands and the p-values are less than 5% except for the Utility Token market cap index for which we conclude that the process is not different from white noise.

The summarized results by each asset class are presented below. These are the results for the market cap indexes while the detailed results for each asset are found in Appendix D (Table of white noise tests). The third and the fifth column below present the percent of assets corresponding to each index that reject the null hypothesis. By way of example, approximately half of the sample in the Indexes of Altcoins, Altchains, Smart Tokens and Utility Tokens reject the null hypothesis of no serial correlation.

Exhibit 6.8: Table of white noise tests

| **Market cap index** | **Q test (p-value)** | **Q-test (3lags). Percent of assets rejecting Ho** | **Breusch-Godfrey test (p-value)** | **Breusch-Godfrey test (5lags). Percent of assets rejecting Ho** |
|---|---|---|---|---|
| Bitcoin Marketcap | 0.0000 | 0.0% | 0.0000 | 0.0% |
| Altcoins Marketcap | 0.0000 | 50.0% | 0.0000 | 58.3% |
| Altchains Marketcap | 0.0000 | 57.9% | 0.0000 | 47.4% |
| Stable Algo Marketcap | 0.0000 | 100.0% | 0.0000 | 100.0% |
| Stable Token Marketcap | 0.0000 | 100.0% | 0.0000 | 100.0% |
| Smart Token Marketcap | 0.0000 | 60.0% | 0.0000 | 60.0% |
| Utility Token Marketcap | 0.7393 | 58.3% | 0.7347 | 66.7% |
| TOTAL Crypto Marketcap | 0.0000 | | 0.0000 | |

### 6.5.2 Tests for independence

We perform non-parametric runs tests to check if the null hypothesis that observations are serially independent, thus produced randomly. This test[10] is important for that our preliminary statistics showed that most daily returns are not normally distributed. A few technical notes. A run is a series of consecutive increasing or decreasing values while the number of these (increasing and decreasing) values is the length of the run. The test first calculates the median return rather the mean return and then counts the number of runs above and below this threshold in each sequence. The total number of observations would be N=$n_0 + n_1$ and the number of runs is r. The test statistic is in the following form

$$z = \frac{r - \mu_r}{\sqrt{\sigma_r^2}}$$

[10]Usually referred to as Wald-Wolfowitz Runs Test

where $\mu_r$ is the expected number of runs computed as follows

$$\mu_r = \frac{2n_0n_1}{N} + 1$$

and $\sigma_r^2$ is the variance computed as follows

$$\sigma_r^2 = \frac{2n_0n_1(2n_0n_1 - N}{N^2(N-1)}$$

The data that will not reject the null hypothesis would allow us to infer that they follow strict white noise process. Recall that failure to support this hypothesis does not entail that data are not white noise. They can be Martingale Difference Sequence (MDS) or Weak White Noise (WWN).

The relevant table is below while detailed results for each asset are located in Appendix D (Table of serially independent tests). The first columns refer to tests applied to composite market cap indexes while the last column show the analysis within each asset class, thus the percent of assets rejecting the null hypothesis.

Exhibit 6.9: Table of serially independent tests

| **Market cap index** | **Run test number of runs** | **Run test (z-stat)** | **Run test (p-value)** | **Run test (percent of assets rejecting Ho)** |
|---|---|---|---|---|
| Bitcoin Marketcap | 409 | -20.1100 | 0.0000 | 0.0% |
| Altcoins Marketcap | 427 | -15.4600 | 0.0000 | 41.7% |
| Altchains Marketcap | 437 | -10.8900 | 0.0000 | 36.8% |
| Stable Algo Marketcap | 427 | -13.9300 | 0.0000 | 100.0% |
| Stable Token Marketcap | 428 | -13.9200 | 0.0000 | 40.0% |
| Smart Token Marketcap | 433 | -13.7600 | 0.0000 | 0.0% |
| Utility Token Marketcap | 411 | 1.1600 | 0.2500 | 33.3% |
| TOTAL Crypto Marketcap | 415 | -19.7000 | 0.0000 | 0.0% |

According to findings, we infer that 21 out of 57 assets reject the null hypothesis for serial independence. In other words, the daily returns of 36% of the assets in our sample are affected by their lagged values, thus the lagged prices can convey some information about the concurrent returns trends of these cryptocurrencies in question, and, consequently, the pricing of these assets seems to be inefficient at the weak level. As said above, for these assets the Weak White Noise (WWN) assumption still holds. Hence, for the remaining 36 assets (the remaining 64%), it can be inferred that data are serially independent and therefore can be either Strict White Noise (SWN) or Martingale Differences Sequence (MDS).

### 6.5.3 Tests for time varying volatility

At this point, the analysis is shifted to addressing volatility clustering by employing ARCH tests, that is Autoregressive Conditional Heteroskedasticity (Engle, 1982). The null hypothesis states that no ARCH effects exist. Having already determined that all series are stationary we can proceed to examine the existence of time-varying volatility, thus that the variance is not constant. But first, we need to decide on the order of the ARCH model. We visually review the partial autocorrelation function (PACF) of squared returns following the assumption that this is an unbiased estimator of the conditional variance (Grek, 2014). We look at the first seven lags of the PACF because seven are the trading days during the week and we decide accordingly for each asset.[11] For the market cap indexes we looked at the first lag. As we might expect, Stable cryptocurrencies (both Algorithmic and Tokens) fail to reject the null hypothesis and, therefore the time-varying hypothesis does not hold. The summarized results are given below while Appendix D (Table of time-varying volatility tests under the column "ARCH-LM test") shows the detailed results for each asset.

Exhibit 6.10: Table of time-varying volatility tests

| **Market cap index** | **ARCH LM test on the index (p-value)** | **percent of assets rejecting Ho: no arch effects** |
|---|---|---|
| Bitcoin Marketcap | 0.0000 | 100.0% |
| Altcoins Marketcap | 0.0000 | 83.3% |
| Altchains Marketcap | 0.0000 | 73.7% |
| Stable Algo Marketcap | 0.3110 | 33.3% |
| Stable Token Marketcap | 0.0636 | 100.0% |
| Smart Token Marketcap | 0.0000 | 40.0% |
| Utility Token Marketcap | 0.0058 | 66.7% |
| TOTAL Crypto Marketcap | 0.0000 | 0.0% |

Approximately 70% of the sample reject the null hypothesis of no time-varying

[11] The number of lags for which the p-value becomes higher that 5% is shown in the detailed table in the Appendix D (Table of time-varying volatility tests).

volatility. Most assets that exhibit conditional heteroskedasticity are Altcoins and Altchains and of course Bitcoin, thus decentralized cryptocurrencies which independently float as opposed to Stable cryptocurrencies which follow a price (exchange rate) rule. What is not expected is the high percentage of Stable Tokens (thus, within this market cap index) that reject the null hypothesis while Algorithmic Stable are less likely to exhibit volatility clustering. A possible explanation is that Stable Tokens are primarily used as a substitute for directly trading Bitcoin. Since the advent of USDTether (USDT), the BTC/USDT pair has replaced the BTC/USD pair as the highest in volume for that ease trading. This time varying volatility could be partly attributed to Bitcoin's volatility clustering but this spillover effect requires formal empirical investigation. An examination of evidence of unusual hype in this trading pair is delivered by Wei (2018a).

## 6.6 Estimation of effects & inferences

Unconditional models for estimation use standard OLS estimation procedure which is not the appropriate one if errors are autocorrelated and the error variances are not constant over time. The former can be addressed with lagged values of the dependent variable (return) and the latter with conditional variance modeling. At this point it is useful to further distinguish between unconditional and conditional moments, thus those that converge to the long-run moments and those of the moments likely to be in the next period[12]. Consequently we expand on the results of the previous section where time varying volatility, thus the presence of ARCH effect was identified. Now, we proceed to apply the issue of modeling the variance of the stochastic term in a non-linear fashion.

The cryptocurrencies shown to exhibit ARCH effects will be next tested for the presence of specialized ARCH family models namely ARCH-M (The letter M stands for in the mean) and EGARCH (The letter E stands for Exponential). At first, we can generalize ARCH models to GARCH (p,q) where the term $h_t$ denotes the conditional variance of a zero mean normally distributed random variable which is equal to the expected value of the square of lagged values of the unconditional variance and the conditional variance. The meaning of this statement can be written in symbolic shorthand as:

$$h_t = \omega + \sum_{i=1}^{q} \alpha_i e_{t-i}^2 + \sum_{j=1}^{p} \beta_j h_{t-j}^2$$

[12]Assume that the error term is a stationary series and follows $e_t = \rho e_{t-1} + u_t$. Now recall that the unconditional mean and variance are zero and $\frac{\sigma^2}{(1-\rho^2)}$ respectively whereas the conditional mean and variance are $\rho e_{t-1}$ and $\sigma_t^2$ respectively.

whereas for $\beta = 0$ the above GARCH model is reduced to an ARCH(p) of order p. This model interpretation is straight-forward; it says that next period's variability (captured by the conditional variance $h_{t+1}$) is a function of the long-term variance ($\omega$), this period's actual variance ($\alpha_i$) and the variance predicted for this period ($\beta_j$). The implied stability constraints of the GARCH specification are: (i) non-negative parameters and (ii) the summation of all parameters are less that unity(Rossi, 2004). In this work, we check that all models abide by these necessary and sufficient conditions for a mean reverting process.

In the main, the traditional version of such family ARCH models assumes that the conditional error distribution is normal (Gausssian). In this spirit, misspecification tests for the standardized and the squared standardized residuals are applied. Nonetheless, it is evident from the preliminary statistics that cryptocurrencies' return possesses substantial kurtosis and skewness. Basically, if the conditional distribution is non-normal and we have incorrectly assumed it is, then the (Maximum Likelihood) estimators are still consistent and asymptotically normal, yet the standard errors will be inconsistent. In the literature there is an ongoing discussion about the appropriate type of distribution for modeling cryptocurrencies' return (Katsiampa et al., 2019).

We can account for "fat tails" in the error distribution by assuming the student-t distribution (Bollerslev, 1987) and the generalised error distribution (GED) as suggested by Nelson (1991). Both extend on the normal distribution for that they have a density function with the property of higher probability of outliers. Note that the t-distribution is used if the associated degrees of freedom are relatively small. If the sample is big, the number of degrees of freedom is big as well an in that case the t-distribution approaches a normal distribution. The generalized error distribution (GED) is a parametric family of symmetric continuous probability distributions. This family allows for tails that are lighter or heavier compared to the normal distribution. Alternatively, it is also suggested the employment of robust standard errors which deals with the non-normality and is known as Quasi Maximum Likelihood (QMLE). Also, autoregressive terms when included in the models aim at correcting for possible effects of non-synchronous trading (Bampinas et al., 2016). In the empirical investigation that follows we consider these varieties and report the model selected.

### 6.6.1 Tests for risk premium effects

The important parameter in the ARCH-in-mean (ARCH-M) models (or GARCH-M in its generalized form) is an additional variable (the variance of the error term) which enters into the mean equation and captures the time-varying risk premium if any to induce a risk-averse agent to hold the longer term asset. The scope is to capture the time-varying risk premium. Written in matrix notation such as: $r_t = b'X_t + \theta h_t + e_t$ where the error term is conditionally heteroskedastic denoted as $\sqrt{h_t}u_t$. The ARCH-M model adds a heteroskedasticity term into the mean equation. Identification of statistical significance accompanied with a positive sign of the parameter $\theta$ entails that there is feedback from the conditional variance to the conditional mean. As we might expect from economic theory, a positive correlation between risk and return should be evident.

We tested the hypothesis for the market cap indexes to get a broader first view. The reported results for the indexes which show the AIC criteria and the estimated coefficient (significance level in parenthesis) for the two types of distributions (QMLE and GED) employed is as follows (not available means that the algorithm did not converge).

Exhibit 6.11: Table of risk premium effects

| **Market cap index** | **coeff. ARCH-M (QMLE)** | **AIC ARCH-M (QMLE)** | **coeff. ARCH-M (GED)** | **AIC ARCH-M (GED)** | **Percent of assets rejecting Ho: no risk premium effects** |
|---|---|---|---|---|---|
| Bitcoin Marketcap | 4.1995*** | -8148 | n/a | n/a | 0.0% |
| Altcoins Marketcap | n/a | n/a | -0.0308 | -4171 | 58.3% |
| Altchains Marketcap | -0.2370 | -2485 | -0.7600 | -4450 | 42.1% |
| Stable Algo Marketcap | -0.0006 | -3325 | n/a | n/a | 0.0% |
| Stable Token Marketcap | n/a | n/a | n/a | n/a | 60.0% |
| Smart Token Marketcap | -0.9226*** | -6178 | n/a | n/a | 40.0% |
| Utility Token Marketcap | 1.1573 | -1927 | 1.1365 | -2083 | 33.3% |
| TOTAL Crypto Marketcap | 3.710*** | -8218 | 2.5611*** | -8947 | |

Risk premium is high in the Bitcoin index displaying substantial positive sign. The same positive sign in found in the Utility Tokens index, though should be treated with conscious for that it's p-value is just above the 10% threshold (not presented here). Negative sign and statistically significant is identified in the Smart Tokens index. This is an interesting result that differentiates Smart Tokens from Utility Tokens with regards to risk premium. It is self-evident that close to the Total Crypto market cap index is the Bitcoin index. A finding aligned with the stylized fact that Bitcoins leads the level of risk in this market. However, results for the other composite indexes are inconclusive for that the coefficients are not statistically significant.. More intuitive results can be derived looking within each index. In addition, the last column presents the percent of assets rejecting the null hypothesis within each market cap index.

As mentioned, the Akaike information criterion estimator compares the results assuming GED distribution to the results assuming QMLE. Consequently, we performed the same test on the 57 cryptocurrencies but for most assets the QMLE estimator was able to conclude the iterations and therefore we used these results (shown in the last column). From the whole sample only 24 out of 57 cryptocurrencies exhibit risk premium effect modeled as ARCH-M at 5% significance level. More accurately, 24 out of 40 cryptocurrencies earlier identified to have time-varying volatility. The ARCH-M test contradicts with the ARCH effects test for volatility clustering in three circumstances (BitcoinSV, EthereumClassic and Tron). We find that the risk premium effect is likely to emerge at Smart Tokens (33% of the sample) and most probably at Altchains and Stable Tokens (close to 60% of the corresponding sub-samples). In Appendix D the detailed results are cited (Table of time-varying volatility tests under the column "ARCH-M (QMLE)").

### 6.6.2 Tests for calendar effects

This part examines whether the weak form of market efficiency in cryptocurrencies is violated by the role of past patterns and seasonality in estimating future prices. There are various cases of calendar effects such as day-of-the-week, month-of-the-year, weekday-of-the month, week-of-the-month, semi-month, turn-of-the-month, end-of-year, holiday-effects. According to Hansen et al. (2005) this effect was first documented by Osborne in 1962. Application of calendar effects test to the financial markets are numerous including equity markets (stocks, indexes), the Foreign Exchange market (currencies) and the commodities market. In the cryptocurrency literature, Kaiser (2019) sets up a sample of ten cryptocurrencies for which seasonality patterns in daily returns are not identified.

We should briefly elaborate on the empirical methodology followed. In the literature, there are two primary models for modeling the day-of-the week effect. The first model is labeled "in-excess return" for weekdays and weekend with unconditional variance specifying a constant premium (b) and a dummy variable associated with each day (i). Thus, $r_{it} - a = b_i D_{it} + e_t$. Rearranging the terms we derive: $r_{it} = a + b_i D_{it} + e_t$ The second model which we use in this work is labeled "average return" for the day-of-the-week effect with conditional variance specifying seven dummy variable associated with all days of the week (i) and no constant to avoid the dummy variable trap. Thus,

$$r_t = \sum_{i=1}^{n} b_i D_{it} + e_t$$

For the models we primarily used arch(1) and garch(1,1) specification (and prefer QMLE estimators) while for the indexes that accepted the null hypothesis of no ARCH effects we employed OLS regression. When garch models violated the additive restriction for the two coefficients (recall need to be non-explosive, thus less than unity) we checked various specifications in accordance with the AIC criteria and chose accordingly. The summarized results are given below while Appendix D (Table of the day-of-the week tests) offers the detailed results for each asset in question.

Exhibit 6.12: Table of calendar effects Panel A

| | Estimated coefficients for in-excess returns | | | | | | |
|---|---|---|---|---|---|---|---|
| **Market cap index** | **Mon** | **Tue** | **Wed** | **Thu** | **Fri** | **Sat** | **Sun** |
| Bitcoin Marketcap | 0.002 | 0.003* | -0.002 | 0.000 | 0.003** | 0.003 | -0.000 |
| Altcoins Marketcap | 0.003 | 0.000 | -0.001 | 0.000 | 0.006* | 0.005** | -0.005** |
| Altchains Marketcap | -0.008 | 0.005 | 0.000 | 0.061*** | 0.009 | 0.005* | -0.000 |
| Stable Algo Marketcap | 0.005 | -0.012* | 0.038*** | 0.034*** | 0.005* | 0.003*** | 0.005 |
| Stable Token Marketcap | 0.003 | 0.014*** | 0.001 | 0.008*** | 0.009** | 0.002*** | 0.001 |
| Smart Token Marketcap | 0.001 | 0.005 | 0.002 | 0.004 | 0.006* | -0.002 | 0.001 |
| Utility Token Marketcap | 0.001 | 0.005 | 0.000 | 0.003 | 0.012* | 0.010 | -0.002 |
| TOTAL Crypto Marketcap | 0.005** | 0.002 | 0.000 | 0.000 | 0.002 | 0.003* | 0.001 |

Exhibit 6.13: Table of calendar effects Panel B

| | Number of assets rejecting Ho: no calendar effects | | | | | | |
|---|---|---|---|---|---|---|---|
| **Market cap index** | **Mon** | **Tue** | **Wed** | **Thu** | **Fri** | **Sat** | **Sun** |
| Bitcoin Marketcap | 0 | 1 | 0 | 0 | 1 | 0 | 0 |
| Altcoins Marketcap | 0 | 1 | 3 | 1 | 5 | 4 | 1 |
| Altchains Marketcap | 0 | 3 | 1 | 5 | 4 | 0 | 2 |
| Stable Algo Marketcap | 0 | 1 | 1 | 1 | 0 | 1 | 0 |
| Stable Token Marketcap | 0 | 0 | 0 | 0 | 1 | 1 | 3 |
| Smart Token Marketcap | 0 | 1 | 0 | 0 | 2 | 1 | 0 |
| Utility Token Marketcap | 0 | 4 | 0 | 2 | 0 | 1 | 2 |
| TOTAL Crypto Marketcap | 0 | 11 | 5 | 9 | 13 | 8 | 8 |
| percent of TOTAL assets rejecting Ho | 0.0% | 19.3% | 8.8% | 15.8% | 22.8% | 14.0% | 14.0% |

According to the results, at 10% significant level the overall crypto-market index imply that we reject the null hypothesis of efficient market in the event of no day-of-the week effect on Monday and Saturday. But, this Monday effect has little to say for that neither appears to other indexes nor to assets individually and it is possibly related to the variation of supply. Notably, all indexes (except for Altchains) and 13 out of 57 assets (13% of the sample) exhibit positive in-excess returns on Friday. This is in line with the stylized fact found in the equities finance literature. Said differently, there is active trading activity going towards the end of the week and even during the Weekend. However, it was unexpected to observe this evidence also in Stable Cryptocurrencies assets.

Looking at the cryptocurrency assets more closely, Stable Tokens allow for in-excess returns from Friday till Sunday possibly in relation to closing crypto-positions (and exchanging Stable Tokens which are primarily used for trading other crypto-assets to US dollars) as on Saturday and Sunday even negative in-excess returns are identified. It should be noted that Stable Algorithmic do not show excess return, an indication that Smart Tokens central bankers offer efficient work. Within this composite index, this is not evident in BitUSD but this seems more like an outlier. In any case the sample is small and need to be extended in the future. Altchains are cryptocurrencies primarily used as means of payment for the execution of decentralized applications (dApps). Nonetheless, these assets do not support the efficient market hypothesis even though their inherent role is not speculative as the day-of-the-week effect is evident 4 out of 7 days of the week. For most Altcoins, the effect is more evident on Friday and Saturday. By and large, this analysis prompts us to think that trading opportunities are not excluded.

### 6.6.3 Tests for leverage effects

In the context of the nature of volatility, an important extension is to study possible asymmetries in its response to past shocks. In finance, it is typical to see volatility more sensitive to negative shocks than to positive shocks of the same magnitude. There are two GARCH models which address this. The Threshold ARCH (TARCH)[13] and the Exponential GARCH (EGARCH) which we use in this work wherein possible leverage effects come in an exponential rather quadratic fashion. The standard EGARCH specification of Nelson (1991) is given as:

$$\log\left(h_t\right) = \omega + a\left|\frac{e_{t-1}}{\sqrt{h_{t-1}}}\right| + \xi \frac{e_{t-1}}{\sqrt{h_{t-1}}} + \beta \log h_{t-1}$$

[13] In the literature, this type of models were introduced by Glosten, Jagannathan, Runkle and are also known as GJR-models when the standard deviation instead of the variance is used in the specification. The GJR GARCH is usually represented by the expression:

$$h_t = \omega + \alpha e_{t-1}^2 + \gamma e_{t-1}^2 I_{t-1} + \beta h_{t-1}$$

where h is the conditional variance, a is the parameter that captures the magnitude effect or the symmetric (garch) effect. $|\beta| < 1$ measures the persistence in conditional volatility irrespective of other market conditions (if large, then volatility takes a long time to die out). The $\xi$ parameter measures the existence of leverage effects. If different from zero, the impact is asymmetric. When it is negative, then negative innovations (bad news) generate more volatility than positive innovations (good news).
Broadly speaking, the literature has been led to the conclusion that financial assets' returns are strongly asymmetric in nature for that negative returns are followed by larger increases in volatility than equally large positive returns (Hentschel, 1995). The results of the test applied to cryptocurrencies are summarized below.

Exhibit 6.14: Table of leverage effects

| **Market cap index** | **coeff. for leverage ($\xi$)** | **p-value** | **coeff. for symmetry (a)** | **p-avlue** | **Percent of assets rejecting Ho: no leverage effects** |
|---|---|---|---|---|---|
| Bitcoin Marketcap | -0.0067 | 0.7550 | 0.2841 | 0.0000 | 0.0% |
| Altcoins Marketcap | -0.1329 | 0.0000 | 0.3464 | 0.0040 | 16.7% |
| Altchains Marketcap | -0.0364 | 0.0850 | 0.0993 | 0.0220 | 5.3% |
| Stable Algo Marketcap | n/a | n/a | n/a | n/a | 0.0% |
| Stable Token Marketcap | -0.2331 | 0.0090 | 0.0449 | 0.6600 | 0.0% |
| Smart Token Marketcap | 0.0929 | 0.0470 | 0.5652 | 0.0000 | 0.0% |
| Utility Token Marketcap | -0.0488 | 0.1020 | 0.1711 | 0.0070 | 16.7% |
| TOTAL Crypto Marketcap | -0.0046 | 0.8040 | 0.2557 | 0.0000 | 0.0% |

The test for leverage effects with regards to Altcoins, Stable Token and Utility Tokens composite market cap indexes indicate that the sign is negative implying that negative innovations result in a higher impact on conditional variance than positive innovation of the same size. This aligns with the stylized fact observed in financial assets. For a negative return shock, the results suggest less returns respectively per dollar (to which are expressed). These effects, for Altcoins and Utility Token indexes are lower than the symmetric effect estimated by the second coefficient in the above table.

The opposite result is found for the Altchains index possibly highlighting similarities with other assets such as commodities. Results for the Bitcoin index (change in market cap) as well for Bitcoin as asset (change in price) and for the TOTAL crypto market cap index are inconclusive. The sign is as anticipated negative but not statistically significant. All selected models were of the form GARCH(1,1) except for Altcoins which were of the form GARCH(1,6). For each assets, the model specification is reported in Appendix D (Table of time-varying tests under the column "EGARCH"). Noticeably, most cryptocurrencies cannot reject the null hypothesis of no leverage effect. Only 5 cryptocurrencies show indication of leverage effect. In more detail, 2 Altcoins (Monero, Decred), 2 Smart Tokens (Holo, BitShares) and 1 Altchain (Ravencoin). The positive sign implies that unanticipated exchange increases are more destabilizing than negative innovations. Still, in these cases the leverage effect does not completely dominate the symmetric effect as measured by the symmetry coefficient.

### 6.6.4 Tests for regime switching effects

While linear models have been popular in studying time series financial assets, advancements on developing and adopting non-linear models are also evident in the last decades. Non-linearity can be modeled in a variety of cases. Models can be (a) linear in mean, yet non-linear in variance such the ARCH family models we examined earlier, (b) non-linear in mean, yet linear in variance and of course (c) non-linear in both mean and variance. Usually in financial assets, the main interest is in modeling the variance in a non-linear fashion due to volatility clustering. The main critique is that most non-linear models use non-linear optimization algorithms that can get stuck at a local optimum in the parameter space or even not being able to find a numerical solution and are largely dependent on the data set to which they apply with the exception of *artificial neural network models*, a machine-learning technique which can deal these issues, though at identification problem expenses (Kuan & White, 1994).

In this analysis we go a step further and employ tests for detecting regime switch in the data of cryptocurrencies earlied identified to exhibit time-varying effects. The most popular case is the *Markov switching model* of Hamilton (1989). This model uses multiple equations that can describe correlated data pertaining different patterns during the period examined. In other words, instead of using one model for the conditional mean or variance of a series, this technique introduces several models to identify different patterns (regimes). This property is useful in volatile markets alike cryptocurrencies. The main idea is to estimate the probability (and in its aftermath the persistence) of possible states even though we do not know the current state of the data generating process as its parameters vary over time. States can be more than two (but always finite) and arrive with different interpretation and economic rationale. Usually two states are sufficient to study for that can be related to easy to understand cases such as high/low volatility while the transition is assumed random and in particular to follow a Markov process. In mathematical notation, the generic model is written as

$$y_t = \mu_{st} + x_t\alpha + z_t\beta_{st} + \epsilon_{st}$$

where,

$y_t$ is the dependent variable (returns in our case)

$\mu_s$ is the state-dependent intercept

$x_t$ is the vector of exogenous variables with state invariant coefficients

$z_t$ is the vector of exogenous variables with state-dependent coefficients $\beta_s$

and the error term is i.i.d with mean zero and state-dependent variance.

We suppose *a priori* there are two states (s=1 or 2). The random variable $s_t$ is discrete and depends only on the immediate past value. We aim at drawing inferences about **changes in mean (positive, negative) and volatility (high, low) between two states** in terms of probability of persistence and duration. Regime classification is probabilistic and determined by data. Application of the Markov switching model to cryptocurrencies is found in Caporale & Zekokh (2019) and Ardia et al. (2019) who only examine Bitcoin to conclude that such models outperform single regime volatility clustering when predicting the Value at Risk (VaR). This section extends by embracing more cryptocurrencies and in relation to the asset class that belong to so as to arrive to useful inferences about changes in mean (positive, negative) and volatility (high, low) between two states in terms of probability of persistence and duration. Note that in the literature, data usually fit into two types of Markov switching models namely Markov switching dynamic regression (MSDR) and Markov switching autoregression (MSAR) which has been the pioneer. We use the former case for that allow a quick adjustment after the process change state. So, we move on to further study the 41 cryptocurrencies identified to exhibit volatility clustering for that our interest is in modeling conditional variance.

The results for each asset class are summarized below while Appendix D (Table of regime switching tests) shows the detailed results for each asset. Reported in the resulted below are the number of coefficients significant at 10% level in state (regime) 1 and state (regime) 2 (column 2 and 3). Next, we show the estimated transition probabilities for state 1 to 1, thus the persistence of not moving to the other state and 2 to 1, thus moving back to state 1. 70% is the cutoff probability level we assumed to show this persistence. The last column shows the pairs of coefficients that change sign that could relate to switch from bear (negative return) to bull sentiment (positive return).

Exhibit 6.15: Table of regime switching effects

| Number of assets rejecting no regime switching effects (significance level 10%) | | | | | |
|---|---|---|---|---|---|
| **Market cap index** | **regime 1** | **regime 2** | **regime 1 with probability over 70%** | **regime 2 with probability over 70%** | **regime of recession (-) / expansion (+)** |
| Bitcoin Marketcap | 1 | 0 | 1 | 0 | 0 |
| Altcoins Marketcap | 8 | 6 | 12 | 1 | 4 |
| Altchains Marketcap | 10 | 11 | 18 | 0 | 5 |
| Stable Algo Marketcap | 0 | 0 | 1 | 0 | 0 |
| Stable Token Marketcap | 3 | 4 | 2 | 0 | 2 |
| Smart Token Marketcap | 0 | 1 | 5 | 0 | 0 |
| Utility Token Marketcap | 4 | 9 | 12 | 1 | 3 |
| TOTAL assets | 26 | 31 | 51 | 2 | 14 |

For two assets (ripple, dogecoin) we preferred to fit dynamic-switching models with two regimes but with a single standard deviation for the entire process while for three assets (Ethereum, SBD, BitUSD) we could not find the existence of two states.

We infer that both regimes are highly persistent and therefore it is highly difficult to identify the superiority of one regime over the other. Only 7 assets show positive sign in both states, thus the two regimes can characterize a moderate-return state and a high-rate state (as mean is higher in state 2). Notably, standard deviation is much higher in state 2 as the models sufficiently capture the two states of high and low volatility clustering. In Appendix D, columns labeled (d1, d2) present the estimated duration of these states (in days). The results suggest that high volatility clustering tend to have lower duration (in days) compared with low volatility clustering duration. On the other hand, for 14 cryptocurrencies returns change states, thus sign (positive to negative) at significance level 10%. Unexpectedly, this is evident also for Stable Token but could be related to asynchronous trading. More often, this change or states can be found in Utility Tokens and less likely in Smart Tokens.

## 6.7 Concluding remarks

The study of peer groups and indexes as the cryptocurrency market grows is becoming highly important for matching investors' tastes and preferences in this alternative markets. The methodological objective of this work is to contribute to examine stylized facts found on daily returns, yet conditional on asset classes to draw inferences within and across composite market indexes. The motivation is to identify similarities and differences in trading activity both across and within these composite indexes. The results support the existence of switch of states (high-low volatility, from negative to positive returns) while do not support the existence of calendar effects on Monday. The less likely anomaly to support is the existence of leverage effects. This work can offer interesting extensions to combine the construction of cryptocurrency market indexes with the employment of predictive models to better monitor the performance of these alternative investments.

# References

Abad, P., Benito, S., & López, C. (2014). A comprehensive review of value at risk methodologies. *The Spanish Review of Financial Economics*, *12*(1), 15–32.

Abadi, J., & Brunnermeier, M. (2018). *Blockchain economics* (Tech. Rep.). National Bureau of Economic Research.

Acquisti, A., Taylor, C., & Wagman, L. (2016). The economics of privacy. *Journal of Economic Literature*, *54*(2), 442–92.

Aizenman, J., Chinn, M. D., & Ito, H. (2013). The âĂIJimpossible trinityâĂİ hypothesis in an era of global imbalances: Measurement and testing. *Review of International Economics*, *21*(3), 447–458.

Alexander, C., Choi, J., Park, H., & Sohn, S. (2019). Bitmex bitcoin derivatives: Price discovery, informational efficiency, and hedging effectiveness. *Journal of Futures Markets*.

Al-Khazali, O., Elie, B., Roubaud, D., et al. (2018). The impact of positive and negative macroeconomic news surprises: Gold versus bitcoin. *Economics Bulletin*, *38*(1), 373–382.

Ammous, S. (2018). Can cryptocurrencies fulfil the functions of money? *The Quarterly Review of Economics and Finance*, *70*, 38–51.

Ankenbrand, T., & Bieri, D. (2018). Assessment of cryptocurrencies as an asset class by their characteristics. *Investment Management & Financial Innovations*, *15*(3), 169.

Antonopoulos, A. M. (2014). *Mastering bitcoin: unlocking digital cryptocurrencies.* “ O’Reilly Media, Inc.”.

Ardia, D., Bluteau, K., & Rüede, M. (2019). Regime changes in bitcoin garch volatility dynamics. *Finance Research Letters*, *29*, 266–271.

Asimakopoulos, S., Lorusso, M., & Ravazzolo, F. (2019). A new economic framework: A dsge model with cryptocurrency.

Bampinas, G., Fountas, S., & Panagiotidis, T. (2016). The day-of-the-week effect is weak: Evidence from the european real estate sector. *Journal of Economics and Finance*, *40*(3), 549–567.

Baran, P. (1964). On distributed communications networks. *IEEE transactions on Communications Systems*, *12*(1), 1–9.

Barber, S., Boyen, X., Shi, E., & Uzun, E. (2012). Bitter to betterâĂŤhow to make bitcoin a better currency. In *International conference on financial cryptography and data security* (pp. 399–414).

Barrdear, J., & Kumhof, M. (2016). The macroeconomics of central bank issued digital currencies.

Bartos, J., et al. (2015). Does bitcoin follow the hypothesis of efficient market? *International Journal of Economic Sciences*, *4*(2), 10–23.

Baumöhl, E. (2019). Are cryptocurrencies connected to forex? a quantile cross-spectral approach. *Finance Research Letters*, *29*, 363–372.

Baur, D. G., & Dimpfl, T. (2018). Asymmetric volatility in cryptocurrencies. *Economics Letters*, *173*, 148–151.

Bech, M. L., & Garratt, R. (2017). Central bank cryptocurrencies. *BIS Quarterly Review September*.

Benigno, P. (2019). Monetary policy in a world of cryptocurrencies.

Benigno, P., Schilling, L. M., & Uhlig, H. (2019). *Cryptocurrencies, currency competition, and the impossible trinity* (Tech. Rep.). National Bureau of Economic Research.

Biais, B., Bisiere, C., Bouvard, M., & Casamatta, C. (2019). The blockchain folk theorem. *The Review of Financial Studies*, *32*(5), 1662–1715.

Biais, B., Bisiere, C., Bouvard, M., Casamatta, C., & Menkveld, A. J. (2018). Equilibrium bitcoin pricing. *Available at SSRN*.

Birch, D. G., & McEvoy, N. A. (1997). Electronic cash-technology will denationalise money. In *International conference on financial cryptography* (pp. 95–108).

Blachand, O. (1990). Why does money affect output. *Handbook of Monetary Economics, Amsterdam, Elsevier*.

Blanchard, O. (2000). What do we know about macroeconomics that fisher and wicksell did not? *De Economist*, *148*(5), 571–601.

Bluedorn, J. C., & Bowdler, C. (2010). The empirics of international monetary transmission: identification and the impossible trinity. *Journal of Money, Credit and Banking*, *42*(4), 679–713.

Böhme, R., Christin, N., Edelman, B., & Moore, T. (2015). Bitcoin: Economics, technology, and governance. *The Journal of Economic Perspectives*, *29*(2), 213–238.

Bollerslev, T. (1987). A conditionally heteroskedastic time series model for speculative prices and rates of return. *The review of economics and statistics*, 542–547.

Bollerslev, T., & Domowitz, I. (1993). Trading patterns and prices in the interbank foreign exchange market. *The Journal of Finance*, *48*(4), 1421–1443.

Bolt, W., & Van Oordt, M. R. (2016). On the value of virtual currencies. *Journal of Money, Credit and Banking*.

Boreiko, D., & Sahdev, N. K. (2018). To ico or not to ico–empirical analysis of initial coin offerings and token sales. *Available at SSRN 3209180*.

Borri, N. (2019). Conditional tail-risk in cryptocurrency markets. *Journal of Empirical Finance*, *50*, 1–19.

Bouoiyour, J., Selmi, R., & Tiwari, A. (2014). Is bitcoin business income or speculative bubble? unconditional vs. conditional frequency domain analysis.

Bouri, E., Molnár, P., Azzi, G., Roubaud, D., & Hagfors, L. I. (2017). On the hedge and safe haven properties of bitcoin: Is it really more than a diversifier? *Finance Research Letters*, *20*, 192–198.

Bouri, E., Shahzad, S. J. H., & Roubaud, D. (2019). Cryptocurrencies as hedges and safe-havens for us equity sectors. *The Quarterly Review of Economics and Finance.*

Box, G. E., & Pierce, D. A. (1970). Distribution of residual autocorrelations in autoregressive-integrated moving average time series models. *Journal of the American statistical Association*, *65*(332), 1509–1526.

Brauneis, A., & Mestel, R. (2019). Cryptocurrency-portfolios in a mean-variance framework. *Finance Research Letters*, *28*, 259–264.

Brito, J., & Castillo, A. (2013). *Bitcoin: A primer for policymakers.* Mercatus Center at George Mason University.

Brunner, K., & Meltzer, A. H. (1971). The uses of money: money in the theory of an exchange economy. *The American Economic Review*, *61*(5), 784–805.

Buchholz, M., Delaney, J., & Warren, J. (2012). Jeff parker economics 312 spring 2012.

Buchholz, M., Delaney, J., Warren, J., & Parker, J. (2012). Bits and bets, information, price volatility, and demand for bitcoin. *Economics*, *312*.

Budish, E. (2018). *The economic limits of bitcoin and the blockchain* (Tech. Rep.). National Bureau of Economic Research.

Caginalp, C. (2018). A dynamical systems approach to cryptocurrency stability. *arXiv preprint arXiv:1805.03143*.

Cagli, E. C. (2019). Explosive behavior in the prices of bitcoin and altcoins. *Finance Research Letters*, *29*, 398–403.

Cahill, D. G., Baur, D. G., Liu, Z. F., & Yang, J. W. (2020). I am a blockchain too: How does the market respond to companiesâĂŹ interest in blockchain? *Journal of Banking & Finance*, 105740.

Calcaterra, C., Kaal, W. A., & Rao, V. K. (2019). Stable cryptocurrencies. *Washington University Journal of Law and Policy*.

Canale, R. R., De Grauwe, P., Foresti, P., & Napolitano, O. (2018). Is there a trade-off between free capital mobility, financial stability and fiscal policy flexibility in the emu? *Review of World Economics*, *154*(1), 177–201.

Caporale, G. M., Gil-Alana, L., & Plastun, A. (2018). Persistence in the cryptocurrency market. *Research in International Business and Finance*, *46*, 141–148.

Caporale, G. M., & Plastun, A. (2018). The day of the week effect in the cryptocurrency market. *Finance Research Letters*.

Caporale, G. M., & Zekokh, T. (2019). Modelling volatility of cryptocurrencies using markov-switching garch models. *Research in International Business and Finance*, *48*, 143–155.

Castronova, E. (2002). On virtual economies.

Castronova, E. (2003). Theory of the avatar.

Catalini, C., & Gans, J. S. (2016). *Some simple economics of the blockchain* (Tech. Rep.). National Bureau of Economic Research.

Chan, S., Chu, J., Nadarajah, S., & Osterrieder, J. (2017). A statistical analysis of cryptocurrencies. *Journal of Risk and Financial Management*, *10*(2), 12.

Cheah, E.-T., & Fry, J. (2015). Speculative bubbles in bitcoin markets? an empirical investigation into the fundamental value of bitcoin. *Economics Letters*, *130*, 32–36.

Chen, C. Y.-H., Härdle, W. K., Hou, A. J., & Wang, W. (2018). Pricing cryptocurrency options: the case of crix and bitcoin. *Available at SSRN 3159130*.

Chinn, M. D., & Ito, H. (2008). A new measure of financial openness. *Journal of comparative policy analysis*, *10*(3), 309–322.

Chiu, J., & Koeppl, T. V. (2017). The economics of cryptocurrencies–bitcoin and beyond. *Available at SSRN 3048124*.

Chu, J., Chan, S., Nadarajah, S., & Osterrieder, J. (2017). Garch modelling of cryptocurrencies. *Journal of Risk and Financial Management*, *10*(4), 17.

Chuen, D. L. K., Guo, L., & Wang, Y. (2017). Cryptocurrency: A new investment opportunity? *The Journal of Alternative Investments*, *20*(3), 16–40.

Ciaian, P., Rajcaniova, M., & Kancs, d. (2016). The economics of bitcoin price formation. *Applied Economics*, *48*(19), 1799–1815.

Coase, R. H. (1960). The problem of social cost. In *Classic papers in natural resource economics* (pp. 87–137). Springer.

Coase, R. H. (1972). Durability and monopoly. *The Journal of Law and Economics*, *15*(1), 143–149.

Cong, L. W., & He, Z. (2019). Blockchain disruption and smart contracts. *The Review of Financial Studies*, *32*(5), 1754–1797.

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

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

Cowen, T., & Kroszner, R. (1987). The development of the new monetary economics. *journal of Political Economy*, *95*(3), 567–590.

D'agostino, R. B., Belanger, A., & D'Agostino Jr, R. B. (1990). A suggestion for using powerful and informative tests of normality. *The American Statistician*, *44*(4), 316–321.

Danielsson, J. (2019). Cryptocurrencies: Policy, economics and fairness. *Systemic Risk Centre Discussion Paper*, *86*, 2018.

Davidson, R., & MacKinnon, J. G. (1981). Several tests for model specification in the presence of alternative hypotheses. *Econometrica: Journal of the Econometric Society*, 781–793.

Davidson, S., De Filippi, P., & Potts, J. (2016). Economics of blockchain. *Available at SSRN 2744751*.

Davies, G. (2010). *History of money*. University of Wales Press.

Detzel, A., Liu, H., Strauss, J., Zhou, G., & Zhu, Y. (2018). Bitcoin: Predictability and profitability via technical analysis. *SSRN Electron. J.*.

Díaz, A., de Córdobab, G. F., & Puchc, L. A. (2019). Money supply for a utility cryptocurrency.

Dickey, D. A., & Fuller, W. A. (1979). Distribution of the estimators for autoregressive time series with a unit root. *Journal of the American statistical association*, *74*(366a), 427–431.

Diebold, F. X., Husted, S., & Rush, M. (1991). Real exchange rates under the gold standard. *Journal of Political Economy*, *99*(6), 1252–1271.

Dodd, N. (2017). The social life of bitcoin. *Theory, Culture & Society*.

Dodd, N. (2018). The social life of bitcoin. *Theory, culture & society*, *35*(3), 35–56.

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.

Dyhrberg, A. H., Foley, S., & Svec, J. (2018). How investible is bitcoin? analyzing the liquidity and transaction costs of bitcoin markets. *Economics Letters*, *171*, 140–143.

Easley, D., O'Hara, M., & Basu, S. (2019). From mining to markets: The evolution of bitcoin transaction fees. *Journal of Financial Economics*.

El Alaoui, M., Bouri, E., & Roubaud, D. (2018). Bitcoin price–volume: A multifractal cross-correlation approach. *Finance Research Letters*.

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of united kingdom inflation. *Econometrica: Journal of the Econometric Society*, 987–1007.

Ernstberger, P. (2009). Linden dollar and virtual monetary policy.

Escanciano, J. C., & Velasco, C. (2006). Testing the martingale difference hypothesis using integrated regression functions. *Computational Statistics & Data Analysis*, *51*(4), 2278–2294.

Evans, C. (2015). Bitcoin in islamic banking and finance. *Journal of Islamic Banking and Finance*, *3*(1), 1–11.

Eyal, I., & Sirer, E. G. (2018). Majority is not enough: Bitcoin mining is vulnerable. *Communications of the ACM*, *61*(7), 95–102.

Fabozzi, F. J. (2009). *Institutional investment management: Equity and bond portfolio strategies and applications* (Vol. 177). John Wiley & Sons.

Fama, E. F. (1980). Banking in the theory of finance. *Journal of monetary economics*, *6*(1), 39–57.

Fama, E. F. (1991). Efficient capital markets: Ii. *The journal of finance*, *46*(5), 1575–1617.

Fama, M., Fumagalli, A., & Lucarelli, S. (2019). Cryptocurrencies, monetary policy, and new forms of monetary sovereignty. *International Journal of Political Economy*, *48*(2), 174–194.

Fantacci, L. (2019). Cryptocurrencies and the denationalization of money. *International Journal of Political Economy*, *48*(2), 105–126.

Fehr, E., & Tyran, J.-R. (2001). Does money illusion matter? *American Economic Review*, *91*(5), 1239–1262.

Fleming, J. M. (1962). Domestic financial policies under fixed and under floating exchange rates. *Staff Papers*, *9*(3), 369–380.

Foley, S., Karlsen, J. R., & Putniņš, T. J. (2019). Sex, drugs, and bitcoin: How much illegal activity is financed through cryptocurrencies? *The Review of Financial Studies*, *32*(5), 1798–1853.

Freixas, X., & Rochet, J.-C. (2008). *Microeconomics of banking*. MIT press.

Friedman, M., & Schwartz, A. J. (1986). Has government any role in money? *journal of Monetary Economics*, *17*(1), 37–62.

Fry, J., & Cheah, E.-T. (2016). Negative bubbles and shocks in cryptocurrency markets. *International Review of Financial Analysis*, *47*, 343–352.

Gandal, N., & Halaburda, H. (2014). Competition in the cryptocurrency market.

Gandal, N., Hamrick, J., Moore, T., & Oberman, T. (2018). Price manipulation in the bitcoin ecosystem. *Journal of Monetary Economics*, *95*, 86–96.

Garcia, D., Tessone, C. J., Mavrodiev, P., & Perony, N. (2014). The digital traces of bubbles: feedback cycles between.

Garratt, R., & Wallace, N. (2018). Bitcoin 1, bitcoin 2,....: An experiment in privately issued outside monies. *Economic Inquiry*, *56*(3), 1887–1897.

Gervais, A., Karame, G. O., Capkun, V., & Capkun, S. (2014). Is bitcoin a decentralized currency? *IEEE security & privacy*, *12*(3), 54–60.

Gkillas, K., & Katsiampa, P. (2018). An application of extreme value theory to cryptocurrencies. *Economics Letters*, *164*, 109–111.

Glaser, F., Zimmermann, K., Haferkorn, M., Weber, M. C., & Siering, M. (2014). Bitcoin-asset or currency? revealing users' hidden intentions. *Revealing Users' Hidden Intentions (April 15, 2014). ECIS*.

Goldfarb, A., & Tucker, C. (2019). Digital economics. *Journal of Economic Literature*, *57*(1), 3–43.

Grek, Å. (2014). *Forecasting accuracy for arch models and garch (1, 1) family: Which model does best capture the volatility of the swedish stock market?*

Griffin, J. M., & Shams, A. (2018). Is bitcoin really un-tethered? *Available at SSRN 3195066*.

Grinberg, R. (2011). Bitcoin: An innovative alternative digital currency. *Hastings Science & Technology Law Journal*, *4*, 160.

Grinberg, R. (2012). Bitcoin: An innovative alternative digital currency. *Hastings Sci. & Tech. LJ*, *4*, 159.

Guesmi, K., Saadi, S., Abid, I., & Ftiti, Z. (2019). Portfolio diversification with virtual currency: Evidence from bitcoin. *International Review of Financial Analysis*, *63*, 431–437.

Gurley, J. G., & Shaw, E. S. (1960). *Money in a theory of finance* (Tech. Rep.).

Hacker, P. (2019). Corporate governance for complex cryptocurrencies? a framework for stability and decision making in blockchain-based organizations.

Hafner, C. (2018). Testing for bubbles in cryptocurrencies with time-varying volatility. *Available at SSRN 3105251*.

Hagen, K. P. (1976). Default risk, homemade leverage, and the modigliani-miller theorem: Note. *The American Economic Review*, *66*(1), 199–203.

Hamilton, J. D. (1989). A new approach to the economic analysis of nonstationary time series and the business cycle. *Econometrica: Journal of the Econometric Society*, 357–384.

Hansen, P. R., Lunde, A., & Nason, J. M. (2005). Testing the significance of calendar effects.

Harvey, C. R. (2016). Cryptofinance. *Available at SSRN 2438299*.

Hayek, F. (1976). *Denationalization of money (institute of economic affairs, london). 1978.*

Hayes, A. (2015). Cryptocurrency value formation: An empirical analysis leading to a cost of production model for valuing bitcoin. *Available at SSRN 2648366*.

Hendrickson, J. R., Hogan, T. L., & Luther, W. J. (2016). The political economy of bitcoin. *Economic Inquiry*, *54*(2), 925–939.

Hendrickson, J. R., & Luther, W. J. (2017). Banning bitcoin. *Journal of Economic Behavior & Organization*, *141*, 188–195.

Hentschel, L. (1995). All in the family nesting symmetric and asymmetric garch models. *Journal of Financial Economics*, *39*(1), 71–104.

Hileman, D. G., & Rauchs, M. (2017). 2017 global cryptocurrency benchmarking study.

Hsieh, Y.-Y., Vergne, J.-P., Anderson, P., Lakhani, K., & Reitzig, M. (2018). Bitcoin and the rise of decentralized autonomous organizations. *Journal of Organization Design*, *7*(1), 14.

Huberman, G., Leshno, J., & Moallemi, C. C. (2019). An economic analysis of the bitcoin payment system. *Columbia Business School Research Paper*(17-92).

Ianiro, A. (2014). A decentralized monetary policy: an analysis of bitcoin in a cash-in-advance model.

Ijiri, Y., et al. (1989). *Momentum accounting and triple-entry bookkeeping: exploring the dynamic structure of accounting measurements* (Tech. Rep.). Carnegie Mellon University, Tepper School of Business.

Irving, F. (1928). The money illusion. *New York: Adelphi Company*.

Iwamura, M., Kitamura, Y., Matsumoto, T., & Saito, K. (2014). Can we stabilize the price of a cryptocurrency?: Understanding the design of bitcoin and its potential to compete with central bank money. *Understanding the Design of Bitcoin and Its Potential to Compete with Central Bank Money (October 25, 2014)*.

Jacobs, G. (2018). Cryptocurrencies and the challenge of global governance. *Cadmus*, *3*(4), 109–123.

Jevons, W. S. (1875). Money and the mechanism of. *Exchange*.

Joseph Jr, M., et al. (2005). Trust in electronic markets: The convergence of cryptographers and economists (originally published in august 1996). *First Monday*.

Kaiser, L. (2019). Seasonality in cryptocurrencies. *Finance Research Letters*, *31*.

Kajtazi, A., & Moro, A. (2019). The role of bitcoin in well diversified portfolios: A comparative global study. *International Review of Financial Analysis*, *61*, 143–157.

Kang, K., & Lee, S. (2018). Money, cryptocurrency, and monetary policy. *Available at SSRN 3303595*.

Kareken, J., & Wallace, N. (1981). On the indeterminacy of equilibrium exchange rates. *The Quarterly Journal of Economics*, *96*(2), 207–222.

Katsiampa, P. (2017). Volatility estimation for bitcoin: A comparison of garch models. *Economics Letters*, *158*, 3–6.

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

Keynes, J. M. (1936). The general theory of money, interest and employment. *Reprinted in The Collected Writings of John Maynard Keynes*, *7*.

Kim, T. (2017). On the transaction cost of bitcoin. *Finance Research Letters*, *23*, 300–305.

Knapp, G. F. (1924). *The state theory of money* (Tech. Rep.). McMaster University Archive for the History of Economic Thought.

Kokenyne, A., Veyrune, R., Habermeier, M. K. F., & Anderson, H. (2009). *Revised system for the classification of exchange rate arrangements* (No. 9-211). International Monetary Fund.

Koning, J. (2016). Fedcoin: a central bank-issued cryptocurrency. *R3 Report*, *15*.

Kristoufek, L. (2013). Bitcoin meets google trends and wikipedia: Quantifying the relationship between phenomena of the internet era. *Scientific reports*, *3*.

Kristoufek, L. (2015). What are the main drivers of the bitcoin price? evidence from wavelet coherence analysis. *PloS one*, *10*(4), e0123923.

Kroll, J. A., Davey, I. C., & Felten, E. W. (2013). The economics of bitcoin mining, or bitcoin in the presence of adversaries. In *Proceedings of weis* (Vol. 2013).

Kuan, C.-M., & White, H. (1994). Artificial neural networks: An econometric perspective. *Econometric reviews*, *13*(1), 1–91.

Kurka, J. (2019). Do cryptocurrencies and traditional asset classes influence each other? *Finance Research Letters*, *31*, 38–46.

Lamport, L., Shostak, R., & Pease, M. (1982). The byzantine generals problem. *ACM Transactions on Programming Languages and Systems (TOPLAS)*, *4*(3), 382–401.

Lehdonvirta, V. (2005). Virtual economics: applying economics to the study of game worlds. In *Proceedings of the 2005 conference on future play (future play 2005), lansing, mi.*

Leibenstein, H. (1950). Bandwagon, snob, and veblen effects in the theory of consumers' demand. *The quarterly journal of economics*, *64*(2), 183–207.

Liu, W. (2019). Portfolio diversification across cryptocurrencies. *Finance Research Letters*, *29*, 200–205.

Ljung, G. M., & Box, G. E. (1978). On a measure of lack of fit in time series models. *Biometrika*, *65*(2), 297–303.

Lucas, R. E. (1980). Equilibrium in a pure currency economy. *Economic inquiry*, *18*(2), 203–220.

Luther, W. J. (2016). Cryptocurrencies, network effects, and switching costs. *Contemporary Economic Policy*, *34*(3), 553–571.

Madan, D. B., Reyners, S., & Schoutens, W. (2019). Advanced model calibration on bitcoin options. *Digital Finance*, 1–21.

Mainelli, M. R., Leitch, M., & Demetis, D. (2019). Economic simulation of cryptocurrencies and their control mechanisms. *Ledger*, *4*.

Malkiel, B. G., & Fama, E. F. (1970). Efficient capital markets: A review of theory and empirical work. *The journal of Finance*, *25*(2), 383–417.

Manuelli, R. E., & Peck, J. (1990). Exchange rate volatility in an equilibrium asset pricing model. *International Economic Review*, 559–574.

Marian, O. Y. (2013). Are cryptocurrencies' super'tax havens?

Markey-Towler, B. (2018). Anarchy, blockchain and utopia: a theory of political-socioeconomic systems organised using blockchain. *Available at SSRN 3095343*.

May, T. (1995). Crypto+ economics+ ai= digital money economies. *Cypherpunks. The Cypherpunks list is archives at http://www. hks. net/cpunks/index. html.*

McNally, S., Roche, J., & Caton, S. (2018). Predicting the price of bitcoin using machine learning. In *2018 26th euromicro international conference on parallel, distributed and network-based processing (pdp)* (pp. 339–343).

Meaning, J., Dyson, B., Barker, J., & Clayton, E. (2018). Broadening narrow money: monetary policy with a central bank digital currency.

Micheler, E. (2015). Custody chains and asset values: why crypto-securities are worth contemplating. *The Cambridge Law Journal*, *74*(03), 505–533.

Mishkin, F. S. (1999). International experiences with different monetary policy regimes). any views expressed in this paper are those of the author only and not those of columbia university or the national bureau of economic research. *Journal of monetary economics*, *43*(3), 579–605.

Mita, M., Ito, K., Ohsawa, S., & Tanaka, H. (2019). What is stablecoin?: A survey on price stabilization mechanisms for decentralized payment systems. *arXiv preprint arXiv:1906.06037*.

Modigliani, F., & Miller, M. H. (1958). The cost of capital, corporation finance and the theory of investment. *The American economic review*, *48*(3), 261–297.

Moin, A., Sirer, E. G., & Sekniqi, K. (2019). A classification framework for stablecoin designs. *arXiv preprint arXiv:1910.10098*.

Mundell, R. A. (1963). Capital mobility and stabilization policy under fixed and flexible exchange rates. *Canadian Journal of Economics and Political Science/Revue canadienne de economiques et science politique*, *29*(4), 475–485.

Myers, S. C., & Majluf, N. S. (1984). Corporate financing and investment decisions when firms have information that investors do not have. *Journal of financial economics*, *13*(2), 187–221.

Nabilou, H., & Prüm, A. (2019). Central banks and regulation of cryptocurrencies. *Review of Banking and Financial Law, Forthcoming*.

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

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

Nakavachara, V., Potipiti, T., & Lertmongkolnam, T. (2019). Should all blockchain-based digital assets be classified under the same asset class? *Available at SSRN 3437279*.

Navia, L. E. (1996). *Classical cynicism: A critical study.* Cambridge Univ Press.

Nelson, D. B. (1991). Conditional heteroskedasticity in asset returns: A new approach. *Econometrica: Journal of the Econometric Society*, 347–370.

Norman, A. L. (1987). A theory of monetary exchange. *The Review of Economic Studies*, *54*(3), 499–517.

Nozick, R. (1974). *Anarchy, state, and utopia* (Vol. 5038). New York: Basic Books.

Obstfeld, M., & Rogoff, K. (2002). Global implications of self-oriented national monetary rules. *The Quarterly journal of economics*, *117*(2), 503–535.

Osterrieder, J., & Lorenz, J. (2017). A statistical risk assessment of bitcoin and its extreme tail behavior. *Annals of Financial Economics*, *12*(01), 1750003.

Panagiotidis, T., Stengos, T., & Vravosinos, O. (2018). On the determinants of bitcoin returns: A lasso approach. *Finance Research Letters*, *27*, 235–240.

Pernice, I. G. A., Henningsen, S., Proskalovich, R., Florian, M., Elendner, H., & Scheuermann, B. (2019). Monetary stabilization in cryptocurrencies-design approaches and open questions. In *Iga pernice, s henningsen, r proskalovich, h elendner and b scheuermann." monetary stabilization in cryptocurrencies-design approaches and open questions" 2019 crypto valley conference on blockchain technology (cvcbt). ieee.*

Peters, G., Panayi, E., & Chapelle, A. (2015). Trends in cryptocurrencies and blockchain technologies: a monetary theory and regulation perspective. *Journal of Financial Perspectives*, *3*(3).

Phillip, A., Chan, J., & Peiris, S. (2019). On long memory effects in the volatility measure of cryptocurrencies. *Finance Research Letters*, *28*, 95–100.

Phillip, A., Chan, J. S., & Peiris, S. (2018). A new look at cryptocurrencies. *Economics Letters*, *163*, 6–9.

Radford, R. A. (1945). The economic organisation of a pow camp. *Economica*, *12*(48), 189–201.

Reagle Jr, J. M., et al. (1996). Trust in electronic markets. *first monday*, *1*(2).

Reis, R., Watson, M. W., et al. (2007). *Measuring changes in the value of the numeraire*. Institute for World Economics.

Ricardo, D. (1816). *Proposals for an economical and secure currency.*

Risius, M., & Spohrer, K. (2017). A blockchain research framework. *Business & Information Systems Engineering*, *59*(6), 385–409.

Rogoff, K. S. (2014). *Costs and benefits to phasing out paper currency* (Tech. Rep.). National Bureau of Economic Research.

Rose, A. K. (1996). Explaining exchange rate volatility: an empirical analysis of âĂŸthe holy trinityâĂŹof monetary independence, fixed exchange rates, and capital mobility. *Journal of International Money and Finance*, *15*(6), 925–945.

Rossi, E. (2004). Lecture notes on garch models. *University of Pavia.*

Samuelson, P. (1965). *Proof that properly anticipated prices fluctuale randomly, lndusrrial management review 6.* Spring.

Schilling, L., & Uhlig, H. (2019). Some simple bitcoin economics. *Journal of Monetary Economics.*

Selgin, G. (2012). Quasi-commodity money.

Selgin, G. (2013). Synthetic commodity money. ssrn scholarly paper id 2000118. *Social Science Research Network, Rochester, NY. http://papers. ssrn. com/abstract*, *2000118*.

Selgin, G. A. (1988). *The theory of free banking: Money supply under competitive note issue.* Rowman & Littlefield pub Inc.

Selgin, G. A., & White, L. H. (1994). How would the invisible hand handle money? *Journal of Economic literature*, *32*(4), 1718–1749.

Senner, R., & Sornette, D. (2019). The holy grail of crypto currencies: Ready to replace fiat money? *Journal of Economic Issues*, *53*(4), 966–1000.

Shafir, E., Diamond, P., & Tversky, A. (1997). Money illusion. *The Quarterly Journal of Economics*, *112*(2), 341–374.

Shen, D., Urquhart, A., & Wang, P. (2019). A three-factor pricing model for cryptocurrencies. *Finance Research Letters.*

Sidrauski, M. (1967). Rational choice and patterns of growth in a monetary economy. *The American Economic Review*, *57*(2), 534–544.

Smit, J., Buekens, F., & Du Plessis, S. (2016). Cigarettes, dollars and bitcoins–an essay on the ontology of money. *Journal of Institutional Economics*, *12*(2), 327–347.

Smith, A. (1776). An inquiry into the nature and causes of the wealth of nations, 2 vols. *W. Strahan and T. Cadell.[MTG].*

Sockin, M., & Xiong, W. (2018). A model of cryptocurrencies. *Unpublished manuscript, Princeton University.*

Sovbetov, Y. (2018). Factors influencing cryptocurrency prices: Evidence from bitcoin, ethereum, dash, litcoin, and monero. *Journal of Economics and Financial Analysis*, *2*(2), 1–27.

Tapscott, D., & Tapscott, A. (2016). *Blockchain revolution: How the technology behind bitcoin is changing money, business, and the world.* Penguin.

Tasca, P., & de Roure, C. (2014). Bitcoin and the ppp puzzle. *Available at SSRN 2461588*.

Trimborn, S., & Härdle, W. K. (2018). Crix an index for cryptocurrencies. *Journal of Empirical Finance*, *49*, 107–122.

Urquhart, A. (2016). The inefficiency of bitcoin. *Economics Letters*, *148*, 80–82.

Urquhart, A. (2018). What causes the attention of bitcoin? *Economics Letters*, *166*, 40–44.

van Wijk, D. (2013). *What can be expected from the bitcoin* (Tech. Rep.). Working paper.

Vaubel, R. (1986). A public choice approach to international organization. *Public Choice*, *51*(1), 39–57.

Vaughn, K. I. (1999). Hayek's implicit economics: rules and the problem of order. *The Review of Austrian Economics*, *11*(1), 129–144.

Verme, P. L. H., & Benavides, R. A. V. (2013). Virtual currencies, micropayments and the payments systems: a challenge to fiat money and monetary policy? *European Scientific Journal, ESJ*, *9*(19).

Vidal-Tomás, D., & Ibañez, A. (2018). Semi-strong efficiency of bitcoin. *Finance Research Letters*, *27*, 259–265.

Vitari, C. (2014). Electronic currencies for purposive degrowth?

Von Mises, L., & Batson, H. E. (1953). *The theory of money and credit* (Vol. 2). Yale University Press New Haven.

Weber, B. (2014). Bitcoin and the legitimacy crisis of money. *Cambridge Journal of Economics*, *40*(1), 17–41.

Wei, W. C. (2018a). The impact of tether grants on bitcoin. *Economics Letters*, *171*, 19–22.

Wei, W. C. (2018b). Liquidity and market efficiency in cryptocurrencies. *Economics Letters*, *168*, 21–24.

Yamaguchi, H. (2004). An analysis of virtual currencies in online games. the japan center for international finance. *Social Science Research Institute, International Christian University. Retrieved from http://papers. ssrn. com/sol3/papers. cfm.*

Yamaguchi, Y., & Yamaguchi, K. (2016). *Peer-to-peer public money system.* Japan Futures Research Center, Working Paper.

Yermack, D. (2013). *Is bitcoin a real currency? an economic appraisal* (Tech. Rep.). National Bureau of Economic Research.

Yermack, D. (2017). Corporate governance and blockchains. *Review of Finance*, *21*(1), 7–31.

Zamfir, V. (2015). What is cryptoeconomics. In *Presentation at crypteconomicon 2015. crypto technology conference, mountain view ca, 26-29 january.*

Zhang, W., Wang, P., Li, X., & Shen, D. (2018). Some stylized facts of the cryptocurrency market. *Applied Economics*, *50*(55), 5950–5965.

Zhu, Y., & Hendry, S. (2018). A framework for analyzing monetary policy in an economy with e-money. *Available at SSRN 3318915*.

# Appendices

# A

# The research puzzle

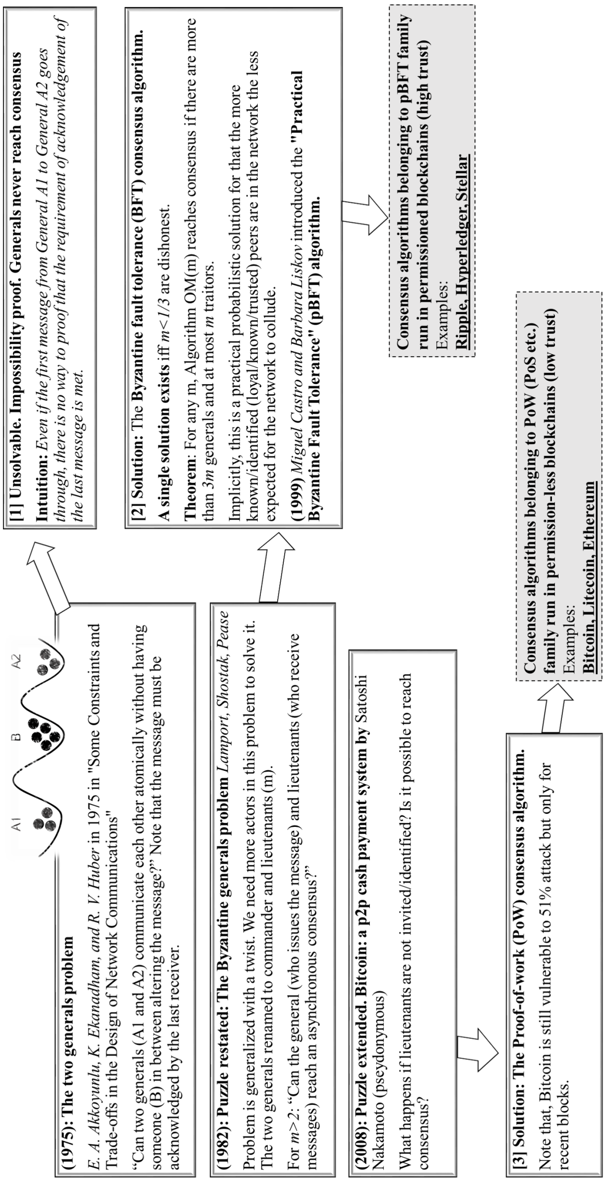



Exhibit A.1: Solutions to the research puzzle

# B

# Consensus algorithms

Exhibit B.1: Description of available algorithms

| **Name and cases** | **Incentive mechanism** |
|---|---|
| *Low trust (networks without permission* | |
| Proof-of-Work (PoW) | Computational power. Expense of CPU time and electricity in order to compete for the reward. |
| Proof-of-Stake (PoS) | Holdings: the probability of creating a block and receiving the associated rewards is proportional to a user's holding of the underlining token or cryptocurrency on the network. For example if you own 1% of the CC, you would be able to mine 1% of all its transactions. |
| Delegated Proof of Stake (DPoS), Proof of Brain (PoB) | Rating system of reputation: Only the top n Witnesses are paid for their service. The top x (lower number than n) earn a regular salary. People's vote power is determined by stake (how many tokens they hold). If a Witness stops doing a quality job securing the network, people in the community can remove their votes. |
| Decred (hybrid PoW and PoS) | Mixed: Proof of stake allow voting and proof of work enables mining. New units of the cryptocurrency are split between PoW miner who found the block, PoS voters on that block and the rest goes towards the Decred Treasury. |
| Proof of Importance (PoI) / Proof of Activity (PoA) | Performance / contribution: Identifying an account's overall impact on the network. For example, in some cryptocurrencies this is done by accounting for three factors: vesting, transaction partners, and number and size of transactions in the last 30 days. |
| Proof-of-Authority (PoA) / RPCA | Identification: It optimizes Proof of Stake model that leverages identity as the form of stake rather than actually staking tokens. The identity is staked by a group of validators (authorities) that are pre-approved to validate transactions and blocks within the respective network. |
| Practical Byzantine Fault Tolerance (pBFT) | No incentive / Faulty tolerance: In order to achieve correctness, given a maximal amount of Byzantine failures, it must be shown that it is impossible for a fraudulent transaction to be confirmed during consensus, unless the number of faulty nodes exceeds that tolerance. |
| *High trust (networks with permission)* | |

# C

# Empirical evidence on cryptocurrencies as alternative investemnts

- Table of risk return profiles (2017-2019)
- Table of correlation matrix by asset class market leaders
- Table of competition between cryptocurrencies against the US Dollar
- Table of competition between cryptocurrencies in relation with Bitcoin
- Table of construction of mean-variance cryptocurrency portfolios

Exhibit C.1: Table of risk return profiles (2017-2019)

| | Daily average return | Risk (standard deviation) | Sharpe ratio (risk free assumed zero) |
|---|---|---|---|
| BITCOIN | 0.287% | 0.0453 | 0.0632 |
| Ethereum | 0.131% | 0.0539 | 0.0244 |
| RIPPLE | 0.333% | 0.0754 | 0.0442 |
| Bitcoin cash | 0.306% | 0.0893 | 0.0342 |
| Litecoin | 0.293% | 0.0645 | 0.0454 |
| Binance coin | 1.039% | 0.0927 | 0.1121 |
| Tether | 0.019% | 0.0072 | 0.0260 |
| EOS | 0.423% | 0.0795 | 0.0532 |
| Bitcoin SV | 0.835% | 0.1193 | 0.0700 |
| MONERO | 0.282% | 0.0648 | 0.0435 |
| STELLAR | 0.490% | 0.0851 | 0.0576 |
| TRON | 0.921% | 0.1216 | 0.0758 |
| CARDANO | 0.578% | 0.1017 | 0.0568 |
| LEO | 0.386% | 0.0440 | 0.0876 |
| Dash | 0.103% | 0.0622 | 0.0166 |

Exhibit C.2: Table of correlation matrix by asset class market leaders

| | BTC/USD | LTC/USD | ETH/USD | BNB/USD | USDT/USD |
|---|---|---|---|---|---|
| BTC/USD | 1,00 | | | | |
| LTC/USD | 0,85 | 1,00 | | | |
| ETH/USD | 0,71 | 0,90 | 1,00 | | |
| BNB/USD | 0,54 | 0,37 | 0,00 | 1,00 | |
| USDT/USD | -0,43 | -0,34 | -0,49 | 0,19 | 1,00 |

Exhibit C.3: Table of competition between cryptocurrencies against the US Dollar

| | 29-Jul-17 | 31-Oct-17 | 31-Jan-18 | 30-Apr-18 | 31-Jul-18 | 31-Oct-18 | 31-Jan-19 | 30-Apr-19 | 27-Jul-19 |
|---|---|---|---|---|---|---|---|---|---|
| **BTC/USD** | 1,00 | 2,37 | 1,58 | 0,90 | 0,84 | 0,81 | 0,55 | 1,55 | 1,77 |
| **LTC/USD** | 1,00 | 1,36 | 2,93 | 0,91 | 0,54 | 0,62 | 0,64 | 2,35 | 1,20 |
| **ETH/USD** | 1,00 | 1,49 | 3,66 | 0,60 | 0,65 | 0,45 | 0,54 | 1,51 | 1,28 |
| **BNB/USD** | 1,00 | 12,15 | 8,51 | 1,28 | 0,96 | 0,68 | 0,67 | 3,53 | 1,26 |
| **USDT/USD** | 1,00 | 1,00 | 0,99 | 1,01 | 1,00 | 0,99 | 1,02 | 1,00 | 0,99 |

Exhibit C.4: Table of competition between cryptocurrencies in relation with Bitcoin

| | 29-Jul-17 | 31-Oct-17 | 31-Jan-18 | 30-Apr-18 | 31-Jul-18 | 31-Oct-18 | 31-Jan-19 | 30-Apr-19 | 27-Jul-19 |
|---|---|---|---|---|---|---|---|---|---|
| BTC/USD | 1,00 | 2,37 | 1,58 | 0,90 | 0,84 | 0,81 | 0,55 | 1,55 | 1,77 |
| BTC/LTC | 1,00 | 1,75 | 0,54 | 0,99 | 1,57 | 1,31 | 0,85 | 0,66 | 1,48 |
| BTC/ETH | 1,00 | 1,60 | 0,43 | 1,51 | 1,30 | 1,78 | 1,01 | 1,02 | 1,38 |
| BTC/BNB | 1,00 | 0,20 | 0,19 | 0,70 | 0,87 | 1,20 | 0,82 | 0,44 | 1,41 |
| BTC/USDT | 1,00 | 2,36 | 1,60 | 0,90 | 0,84 | 0,82 | 0,54 | 1,55 | 1,79 |

Exhibit C.5: Table of construction of mean-variance cryptocurrency portfolios

| | Weight Bitcoin | Weight Litecoin | Weight Ethereum | Weight Binance | Weight USDTether | mean | variance | std deviation |
|---|---|---|---|---|---|---|---|---|
| naïve (1/N) portfolio | 20% | 20% | 20% | 20% | 20% | 0.37% | 0.18% | 0.04189 |
| market cap index portfolio | 73% | 3% | 22% | 1% | 1% | 0.26% | 0.19% | 0.04401 |
| volume index portfolio | 45% | 6% | 18% | 1% | 31% | 0.18% | 0.10% | 0.03145 |
| min variance portfolio | 26% | 0% | 27% | 0% | 48% | 0.11% | 0.06% | 0.02456 |
| BTC | 100% | 0% | 0% | 0% | 0% | 0.28% | 0.21% | 0.04534 |
| LTC | 0% | 100% | 0% | 0% | 0% | 0.30% | 0.42% | 0.06451 |
| ETH | 0% | 0% | 100% | 0% | 0% | 0.15% | 0.29% | 0.05398 |
| BNB | 0% | 0% | 0% | 100% | 0% | 1.14% | 0.86% | 0.09253 |
| USDT | 0% | 0% | 0% | 0% | 100% | 0.00% | 0.00% | 0.00704 |
| Efficient 1 | 55% | 38% | -108% | 111% | 4% | 1.37% | 1.11% | 0.10519 |
| Efficient 2 | 50% | 0% | 0% | 0% | 50% | 0.14% | 0.05% | 0.02335 |

# D

# Empirical tests on the weak form efficiency of cryptocurrencies

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- Table of regime switching tests Panel B

Exhibit D.1: Table of summary statistics Panel A

| Asset | Ticker | class | Name of asset class | of assets | observations | mean | Max | Min | deviation | kurtosis | skewness | downside risk | VaR (5%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| bitcoin | BTC | 1 | D Bitcoin | 28-Apr-13 | 2,284 | 0.003 | 0.417 | -0.229 | 0.043 | 9.274 | 0.465 | 0.033 | -0.064 |
| ethereum | ETH | 3 | D Altchains | 7-Aug-15 | 1,453 | 0.005 | 0.511 | -0.730 | 0.070 | 13.871 | 0.212 | 0.037 | -0.090 |
| ripple | XRP | 6 | C Smart Token | 4-Aug-13 | 2,186 | 0.005 | 1.788 | -0.452 | 0.085 | 104.621 | 6.219 | 0.042 | -0.090 |
| bitcoincash | BCH | 2 | D Altcoins | 23-Jul-17 | 737 | 0.003 | 0.546 | -0.357 | 0.089 | 8.946 | 1.606 | 0.030 | -0.118 |
| litecoin | LTC | 2 | D Altcoins | 30-Jun-14 | 1,856 | 0.003 | 0.670 | -0.401 | 0.060 | 18.135 | 1.997 | 0.034 | -0.079 |
| BinanceCoin | BNB | 7 | C Utility Token | 25-Jul-17 | 735 | 0.010 | 0.966 | -0.335 | 0.093 | 22.385 | 2.859 | 0.027 | -0.098 |
| tether | USDT | 5 | C Stable Token | 2-Mar-15 | 1,611 | 0.000 | 0.062 | -0.046 | 0.006 | 22.824 | 1.200 | 0.003 | -0.010 |
| eos | EOS | 3 | D Altchains | 1-Jul-17 | 759 | 0.006 | 1.719 | -0.320 | 0.104 | 98.369 | 6.476 | 0.029 | -0.117 |
| bitcoinsv | BSV | 2 | D Altcoins | 9-Nov-18 | 263 | 0.008 | 0.896 | -0.468 | 0.119 | 19.168 | 2.837 | 0.020 | -0.117 |
| monero | XMR | 2 | D Altcoins | 30-Jun-14 | 1,856 | 0.004 | 0.794 | -0.256 | 0.071 | 13.840 | 1.716 | 0.039 | -0.102 |
| stellar | XLM | 6 | C Smart Token | 17-Jul-14 | 1,839 | 0.005 | 1.054 | -0.303 | 0.086 | 37.091 | 3.967 | 0.039 | -0.099 |
| tron | TRX | 3 | D Altchains | 13-Sep-17 | 685 | 0.009 | 1.191 | -0.316 | 0.121 | 34.032 | 4.230 | 0.031 | -0.126 |
| cardano | ADA | 3 | D Altchains | 1-Oct-17 | 667 | 0.006 | 1.365 | -0.241 | 0.101 | 62.557 | 5.674 | 0.025 | -0.106 |
| unus sed leo | LEO | 6 | C Smart Token | 21-May-19 | 70 | 0.004 | 0.129 | -0.075 | 0.043 | 0.610 | 0.520 | 0.004 | -0.071 |
| dash | DASH | 2 | D Altcoins | 30-Jun-14 | 1,856 | 0.003 | 1.142 | -0.347 | 0.068 | 48.290 | 3.516 | 0.035 | -0.085 |
| tezos | XTZ | 3 | D Altchains | 2-Oct-17 | 666 | 0.003 | 0.763 | -0.363 | 0.081 | 13.055 | 1.376 | 0.028 | -0.106 |
| chainlink | LINK | 6 | C Smart Token | 20-Sep-17 | 678 | 0.007 | 0.623 | -0.260 | 0.091 | 5.993 | 1.337 | 0.029 | -0.116 |
| neo | NEO | 3 | D Altchains | 9-Sep-16 | 1,054 | 0.009 | 2.077 | -0.407 | 0.121 | 93.260 | 6.561 | 0.038 | -0.114 |
| iota | MIOTA | 3 | D Altchains | 13-Jun-17 | 777 | 0.002 | 0.460 | -0.321 | 0.082 | 5.025 | 0.843 | 0.031 | -0.118 |
| ethclass | ETC | 3 | D Altchains | 24-Jul-16 | 1,101 | 0.006 | 3.217 | -0.354 | 0.121 | 456.713 | 17.288 | 0.033 | -0.097 |
| cosmos | ATOM | 3 | D Altchains | 14-Mar-19 | 138 | 0.000 | 0.288 | -0.351 | 0.084 | 3.807 | -0.179 | 0.062 | -0.118 |
| nem | XEM | 3 | D Altchains | 1-Apr-15 | 1,581 | 0.007 | 1.721 | -0.395 | 0.096 | 71.459 | 4.950 | 0.041 | -0.110 |
| maker | MKR | 6 | C Smart Token | 3-Nov-17 | 634 | 0.003 | 0.568 | -0.294 | 0.067 | 11.274 | 1.413 | 0.022 | -0.093 |
| ontology | ONT | 3 | D Altchains | 8-Mar-18 | 509 | 0.001 | 0.587 | -0.425 | 0.080 | 8.390 | 1.051 | 0.025 | -0.114 |
| crypto.comchain | CRO | 7 | C Utility Token | 25-Nov-18 | 247 | 0.009 | 1.383 | -0.215 | 0.128 | 56.212 | 5.958 | 0.016 | -0.119 |
| usdcoin | USDC | 5 | C Stable Token | 8-Oct-18 | 295 | 0.000 | 0.020 | -0.022 | 0.006 | 2.164 | -0.175 | 0.006 | -0.010 |
| zcash | ZEC | 2 | D Altcoins | 29-Oct-16 | 1,004 | 0.000 | 1.846 | -0.715 | 0.098 | 131.401 | 6.578 | 0.039 | -0.109 |
| vsystems | VSYS | 3 | D Altchains | 5-Mar-19 | 147 | 0.018 | 0.546 | -0.159 | 0.086 | 14.058 | 2.801 | 0.009 | -0.080 |
| dogecoin | DOGE | 2 | D Altcoins | 15-Dec-13 | 2,053 | 0.004 | 1.942 | -0.467 | 0.089 | 119.773 | 6.437 | 0.045 | -0.095 |
| vechain | VET | 3 | D Altchains | 3-Aug-18 | 361 | -0.001 | 0.421 | -0.212 | 0.065 | 8.677 | 1.314 | 0.041 | -0.102 |

Exhibit D.2: Table of summary statistics Panel B

| Asset | Ticker | class | Name of asset class | of assets | observations | mean | Max | Min | deviation | kurtosis | skewness | downside risk | VaR (5%) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| decred | DCR | 2 | D Altcoins | 10-Feb-16 | 1,266 | 0.006 | 0.539 | -0.276 | 0.081 | 7.025 | 1.685 | 0.034 | -0.106 |
| basicattention | BAT | 7 | C Utility Token | 1-Jun-17 | 789 | 0.003 | 0.720 | -0.300 | 0.082 | 8.103 | 1.173 | 0.031 | -0.112 |
| btcgold | BTG | 2 | D Altcoins | 23-Oct-17 | 645 | -0.001 | 1.004 | -0.713 | 0.094 | 35.057 | 2.570 | 0.062 | -0.107 |
| huobitoken | HT | 7 | C Utility Token | 3-Feb-18 | 542 | 0.004 | 0.386 | -0.162 | 0.057 | 5.757 | 1.148 | 0.017 | -0.085 |
| qtum | QTUM | 3 | D Altchains | 24-May-17 | 797 | 0.003 | 0.748 | -0.363 | 0.093 | 15.323 | 2.235 | 0.032 | -0.119 |
| hedgetrade | HEDGE | 6 | C Smart Token | 26-Feb-19 | 154 | 0.018 | 0.434 | -0.617 | 0.109 | 10.674 | -1.155 | 0.020 | -0.079 |
| egretia | EGT | 6 | C Smart Token | 2-Jul-18 | 393 | 0.010 | 0.463 | -0.329 | 0.099 | 3.340 | 0.898 | 0.024 | -0.132 |
| trueusd | TUSD | 5 | C Stable Token | 6-Mar-18 | 511 | 0.000 | 0.079 | -0.083 | 0.008 | 34.314 | -0.072 | 0.003 | -0.010 |
| paxos | PAX | 5 | C Stable Token | 27-Sep-18 | 306 | 0.000 | 0.020 | -0.016 | 0.005 | 2.631 | 0.384 | 0.004 | -0.010 |
| omisego | OMG | 3 | D Altchains | 14-Jul-17 | 746 | 0.005 | 0.741 | -0.265 | 0.089 | 15.435 | 2.200 | 0.029 | -0.116 |
| kucoinshares | KCS | 7 | C Utility Token | 24-Oct-17 | 644 | 0.005 | 0.973 | -0.242 | 0.093 | 28.176 | 3.330 | 0.026 | -0.116 |
| ravencoin | RVN | 3 | D Altchains | 10-Mar-18 | 507 | 0.004 | 0.762 | -0.285 | 0.090 | 11.509 | 1.872 | 0.024 | -0.113 |
| lisk | LSK | 3 | D Altchains | 6-Apr-16 | 1,210 | 0.007 | 1.518 | -0.811 | 0.129 | 45.443 | 4.145 | 0.052 | -0.108 |
| bitcoindiamond | BCD | 2 | D Altcoins | 24-Nov-17 | 613 | 0.004 | 3.211 | -0.694 | 0.187 | 146.299 | 9.175 | 0.042 | -0.156 |
| nano | NANO | 2 | D Altcoins | 22-Mar-17 | 860 | 0.011 | 1.112 | -0.297 | 0.120 | 15.303 | 2.513 | 0.038 | -0.138 |
| bittorrent | BTT | 6 | C Smart Token | 31-Jan-19 | 180 | 0.005 | 0.391 | -0.198 | 0.071 | 8.485 | 1.926 | 0.011 | -0.086 |
| energi | NRG | 3 | D Altchains | 24-Aug-18 | 340 | 0.012 | 0.388 | -0.209 | 0.091 | 2.223 | 0.998 | 0.019 | -0.116 |
| educare | EKT | 6 | C Smart Token | 24-Jan-18 | 552 | 0.007 | 1.285 | -0.461 | 0.120 | 41.448 | 4.386 | 0.029 | -0.114 |
| waves | WAVES | 3 | D Altchains | 2-Jun-16 | 1,153 | 0.003 | 0.466 | -0.520 | 0.078 | 6.134 | 0.283 | 0.039 | -0.113 |
| holo | HOT | 6 | C Smart Token | 30-Apr-18 | 456 | 0.005 | 0.482 | -0.240 | 0.086 | 6.130 | 1.632 | 0.021 | -0.112 |
| lambda | LAMB | 6 | C Smart Token | 2-Jan-19 | 209 | 0.023 | 0.844 | -0.274 | 0.116 | 14.014 | 2.768 | 0.014 | -0.094 |
| hypercash | HC | 2 | D Altcoins | 20-Aug-17 | 709 | 0.002 | 0.976 | -0.565 | 0.105 | 16.036 | 1.839 | 0.036 | -0.136 |
| dai (sai) | SAI | 4 | D Stable Algorithmic | 26-Jan-18 | 550 | 0.001 | 0.284 | -0.065 | 0.019 | 99.311 | 6.447 | 0.005 | -0.020 |
| bitusd | BITUSD | 4 | D Stable Algorithmic | 1-Nov-14 | 1,732 | 0.008 | 5.019 | -0.917 | 0.197 | 348.520 | 16.534 | 0.065 | -0.071 |
| sbd | SBD | 4 | D Stable Algorithmic | 18-Jul-16 | 1,107 | 0.004 | 3.182 | -0.765 | 0.125 | 386.972 | 15.592 | 0.053 | -0.095 |
| bitshares | BTS | 6 | C Smart Token | 21-Jul-14 | 1,835 | 0.004 | 0.690 | -0.322 | 0.079 | 12.804 | 1.997 | 0.044 | -0.102 |
| Digix Gold token | DGX | 5 | C Stable Token | 15-May-18 | 441 | 0.001 | 0.253 | -0.158 | 0.040 | 5.156 | 0.543 | 0.012 | -0.063 |
| **Grand Total** | | | **Asset class** | **57** | **49,349** | **0.0052** | **0.9944** | **-0.3506** | **0.0863** | **49.9456** | **3.2999** | **0.0295** | **-0.0965** |
| ***D Bitcoin*** | | | ***D Bitcoin*** | 1 | 2,284 | 0.003 | 0.417 | -0.229 | 0.043 | 9.274 | 0.465 | 0.033 | -0.064 |
| ***D Altcoins*** | | | ***D Altcoins*** | 12 | 13,718 | 0.004 | 1.223 | -0.463 | 0.098 | 48.273 | 3.539 | 0.038 | -0.112 |
| ***D Altchains*** | | | ***D Altchains*** | 19 | 14,651 | 0.005 | 1.026 | -0.371 | 0.094 | 51.544 | 3.386 | 0.033 | -0.110 |
| ***D Stable Algorithmic*** | | | ***D Stable Algorithmic*** | 3 | 3,389 | 0.004 | 2.828 | -0.582 | 0.114 | 278.268 | 12.858 | 0.041 | -0.062 |
| ***C Stable Token*** | | | ***C Stable Token*** | 5 | 3,164 | 0.000 | 0.087 | -0.065 | 0.013 | 13.418 | 0.376 | 0.006 | -0.020 |
| ***C Utility Token*** | | | ***C Utility Token*** | 5 | 2,957 | 0.006 | 0.886 | -0.251 | 0.091 | 24.127 | 2.894 | 0.023 | -0.106 |
| ***C Smart Token*** | | | ***C Smart Token*** | 12 | 9,186 | 0.008 | 0.729 | -0.319 | 0.088 | 21.374 | 2.159 | 0.025 | -0.099 |

Exhibit D.3: Table of ADF tests for stationarity Panel A

| | | | | levels DF test (no lags) | | | ADF test | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Asset** | **Ticker** | **class** | **Name of asset class** | **Trend** | **Drift** | **constant** | ***Lags*** | **Trend** | **Drift** | **constant** |
| bitcoin | BTC | 1 | D Bitcoin | -48.015*** | -48.025*** | -47.851*** | 5 | -17.362*** | -17.366 *** | -17.124*** |
| ethereum | ETH | 3 | D Altchains | -35.563*** | -35.500*** | -35.326*** | 5 | -15.673*** | -15.563*** | -15.298*** |
| ripple | XRP | 6 | C Smart Token | -44.189*** | -44.199*** | -44.083*** | 7 | -13.765 *** | -13.768*** | -13.631*** |
| bitcoincash | BCH | 2 | D Altcoins | -23.633*** | -23.624*** | -23.616*** | 5 | -10.439 *** | -10.400 *** | -10.368*** |
| litecoin | LTC | 2 | D Altcoins | -41.652*** | -41.634*** | 41.567*** | 5 | -15.123*** | -15.103*** | -15.007*** |
| BinanceCoin | BNB | 7 | C Utility Token | -22.634*** | -22.442*** | -22.227*** | 5 | -8.377*** | -8.186*** | -7.998*** |
| tether | USDT | 5 | C Stable Token | -48.282*** | -48.297*** | -48.281*** | 5 | -18.348*** | -18.348 *** | -18.324*** |
| eos | EOS | 3 | D Altchains | -24.842*** | -24.770*** | -24.713*** | 5 | -11.750 *** | -11.750 *** | -11.710*** |
| bitcoinsv | BSV | 2 | D Altcoins | -16.406*** | 16.431*** | -16.373*** | 5 | -8.234*** | -8.217*** | -8.184*** |
| monero | XMR | 2 | D Altcoins | -43.554*** | -43.564*** | -43.436*** | 5 | -14.427*** | -14.429*** | -14.283*** |
| stellar | XLM | 6 | C Smart Token | -37.298*** | -37.308*** | -37.205*** | | | | |
| tron | TRX | 3 | D Altchains | -24.365*** | -24.178*** | -24.069*** | 2 | -11.971*** | -11.807 *** | -11.713*** |
| cardano | ADA | 3 | D Altchains | -24.240*** | -24.098*** | -24.051*** | 2 | -11.621*** | -11.491*** | -11.445*** |
| unus sed leo | LEO | 6 | C Smart Token | -9.287*** | -8.247*** | -8.213*** | 2 | -3.783*** | -3.217*** | -3.202 *** |
| dash | DASH | 2 | D Altcoins | -44.496*** | -44.507*** | -44.411*** | 1 | -32.287*** | -32.294*** | -32.175*** |
| tezos | XTZ | 3 | D Altchains | -25.136*** | -25.116*** | -25.101*** | 1 | -16.555*** | -16.532*** | -16.513*** |
| chainlink | LINK | 6 | C Smart Token | -25.794*** | -25.811*** | -25.675*** | | | | |
| neo | NEO | 3 | D Altchains | -39.340*** | -39.265*** | -39.111*** | 2 | -17.279*** | -17.184*** | -17.037*** |
| iota | MIOTA | 3 | D Altchains | -26.826*** | -26.783*** | -26.781*** | 2 | -14.630*** | -14.543*** | -14.523 *** |
| ethclass | ETC | 3 | D Altchains | -39.236*** | -39.097*** | -39.013*** | | | | |
| cosmos | ATOM | 3 | D Altchains | -13.104*** | -13.151*** | -13.199*** | | | | |
| nem | XEM | 3 | D Altchains | -42.609*** | -42.563*** | -42.338*** | 4 | -16.395*** | -16.327*** | -16.052*** |
| maker | MKR | 6 | C Smart Token | -24.735*** | -24.689*** | -24.660*** | | | | |
| ontology | ONT | 3 | D Altchains | -21.965*** | -21.973*** | -21.991*** | | | | |
| crypto.comchain | CRO | 7 | C Utility Token | -14.105*** | -14.100*** | -14.060*** | 2 | -6.918*** | -6.880*** | -6.821*** |
| usdcoin | USDC | 5 | C Stable Token | -25.033*** | -25.073*** | -25.094*** | | | | |
| zcash | ZEC | 2 | D Altcoins | -34.603*** | -34.621*** | -34.638*** | 2 | -19.272*** | -19.285*** | -19.300*** |
| vsystems | VSYS | 3 | D Altchains | -14.873*** | -14.744*** | -14.059*** | 3 | -4.806*** | -4.623*** | -4.110 *** |
| dogecoin | DOGE | 2 | D Altcoins | -41.365*** | -41.369*** | -41.289*** | 2 | -28.268*** | -28.267*** | -28.149*** |
| vechain | VET | 3 | D Altchains | -20.569*** | -20.583*** | -20.608*** | | | | |

*Notes: (*) significant at 10 %; (**) significant at 5%; (***) significant at 1%.*

Exhibit D.4: Table of ADF tests for stationarity Panel B

| | | | | levels DF test (no lags) | | | ADF test | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Asset** | **Ticker** | **class** | **Name of asset class** | **Trend** | **Drift** | **constant** | ***Lags*** | **Trend** | **Drift** | **constant** |
| decred | DCR | 2 | D Altcoins | -39.490*** | -39.412*** | -39.189*** | | | | |
| basicattention | BAT | 7 | C Utility Token | -29.743*** | -29.741*** | -29.703*** | | | | |
| btcgold | BTG | 2 | D Altcoins | -25.738*** | -25.758*** | -25.776*** | | | | |
| huobitoken | HT | 7 | C Utility Token | -22.983*** | -23.004*** | -22.923*** | | | | |
| qtum | QTUM | 3 | D Altchains | -25.791*** | -25.751*** | -25.744*** | | | | |
| hedgetrade | HEDGE | 6 | C Smart Token | -13.241*** | -13.224*** | -12.883*** | 2 | -5.351*** | -5.334*** | -5.081*** |
| egretia | EGT | 6 | C Smart Token | -19.235*** | -18.149*** | -18.011*** | | | | |
| trueusd | TUSD | 5 | C Stable Token | -36.636*** | -36.613*** | -36.646*** | 2 | -17.201*** | -17.175*** | -17.193*** |
| paxos | PAX | 5 | C Stable Token | -21.584*** | -21.618*** | -21.653*** | 1 | -15.770*** | -15.795** | -15.821*** |
| omisego | OMG | 3 | D Altchains | -26.662*** | -26.341*** | -26.290*** | | | | |
| kucoinshares | KCS | 7 | C Utility Token | -22.545*** | -22.528*** | -22.491*** | 5 | -7.004*** | -7.002*** | -6.975*** |
| ravencoin | RVN | 3 | D Altchains | -22.138*** | -22.158*** | -22.138*** | 5 | -7.437*** | -7.445*** | -7.402*** |
| lisk | LSK | 3 | D Altchains | -42.671*** | -42.524*** | -42.419*** | 2 | -19.847*** | -19.718*** | -19.622*** |
| bitcoindiamond | BCD | 2 | D Altcoins | -25.937*** | -25.945*** | -25.955*** | 1 | -21.087*** | -21.093*** | -21.099*** |
| nano | NANO | 2 | D Altcoins | -27.123*** | -26.947*** | -26.751*** | 1 | -18.358*** | -18.196*** | -18.014*** |
| bittorrent | BTT | 6 | C Smart Token | -10.836*** | -10.745*** | -10.732*** | | | | |
| energi | NRG | 3 | D Altchains | -20.303*** | -20.330*** | -20.037*** | | | | |
| educare | EKT | 6 | C Smart Token | -26.897*** | -26.753*** | -26.701*** | 3 | -9.636*** | -9.493*** | -9.442*** |
| waves | WAVES | 3 | D Altchains | -32.036*** | -32.039*** | -32.019*** | | | | |
| holo | HOT | 6 | C Smart Token | -20.290*** | -20.297*** | -20.266*** | | | | |
| lambda | LAMB | 6 | C Smart Token | -11.449*** | -11.481*** | -11.168*** | | | | |
| hypercash | HC | 2 | D Altcoins | -28.196*** | -28.215*** | -28.222*** | | | | |
| dai (sai) | SAI | 4 | D Stable Algorithmic | -33.646*** | -33.638*** | -33.579*** | 3 | -14.788*** | -14.759*** | -14.647*** |
| bitusd | BITUSD | 4 | D Stable Algorithmic | -54.983*** | -54.675*** | -54.562*** | 5 | -9.016*** | -8.913*** | -8.873*** |
| sbd | SBD | 4 | D Stable Algorithmic | -38.209*** | -38.226*** | -38.204*** | | | | |
| bitshares | BTS | 6 | C Smart Token | -40.012*** | -40.023*** | -39.960*** | 1 | -26.558*** | -26.565*** | -26.498*** |
| Digix Gold token | DGX | 5 | C Stable Token | -30.416*** | -30.445*** | -30.443*** | 5 | -11.873*** | -11.871*** | -11.765*** |
| **Grand Total** | | | **Asset class** | **57** | **57** | **57** | **57** | **57** | **57** | **57** |
| ***D Bitcoin*** | | | ***D Bitcoin*** | 1 | 1 | 1 | 1 | 1 | 1 | 1 |
| ***D Altcoins*** | | | ***D Altcoins*** | 12 | 12 | 12 | 12 | 12 | 12 | 12 |
| ***D Altchains*** | | | ***D Altchains*** | 19 | 19 | 19 | 19 | 19 | 19 | 19 |
| ***D Stable Algorithmic*** | | | ***D Stable Algorithmic*** | 3 | 3 | 3 | 3 | 3 | 3 | 3 |
| ***C Stable Token*** | | | ***C Stable Token*** | 5 | 5 | 5 | 5 | 5 | 5 | 5 |
| ***C Utility Token*** | | | ***C Utility Token*** | 5 | 5 | 5 | 5 | 5 | 5 | 5 |
| ***C Smart Token*** | | | ***C Smart Token*** | 12 | 12 | 12 | 12 | 12 | 12 | 12 |

*Notes: (*) significant at 10 %; (**) significant at 5%; (***) significant at 1%.*

Exhibit D.5: Table of white noise tests Panel A

| Asset | Ticker | class | Name of asset class | Portmanteau test for white noise (3 lags) | Breusch-Godfrey test (5lags) |
|---|---|---|---|---|---|
| bitcoin | BTC | 1 | D Bitcoin | 0.8345 | 0.0652 |
| ethereum | ETH | 3 | D Altchains | 0.0056 | 0.0062 |
| ripple | XRP | 6 | C Smart Token | 0.0001 | 0.0000 |
| bitcoincash | BCH | 2 | D Altcoins | 0.0013 | 0.0034 |
| litecoin | LTC | 2 | D Altcoins | 0.1439 | 0.0798 |
| BinanceCoin | BNB | 7 | C Utility Token | 0.0000 | 0.0000 |
| tether | USDT | 5 | C Stable Token | 0.0000 | 0.0000 |
| eos | EOS | 3 | D Altchains | 0.0352 | 0.0849 |
| bitcoinsv | BSV | 2 | D Altcoins | 0.2168 | 0.0811 |
| monero | XMR | 2 | D Altcoins | 0.7706 | 0.0014 |
| stellar | XLM | 6 | C Smart Token | 0.0000 | 0.0000 |
| tron | TRX | 3 | D Altchains | 0.0000 | 0.0001 |
| cardano | ADA | 3 | D Altchains | 0.0000 | 0.0000 |
| unus sed leo | LEO | 6 | C Smart Token | 0.1379 | 0.3282 |
| dash | DASH | 2 | D Altcoins | 0.1503 | 0.1535 |
| tezos | XTZ | 3 | D Altchains | 0.0165 | 0.0351 |
| chainlink | LINK | 6 | C Smart Token | 0.8969 | 0.5742 |
| neo | NEO | 3 | D Altchains | 0.0956 | 0.1376 |
| iota | MIOTA | 3 | D Altchains | 0.0517 | 0.0936 |
| ethclass | ETC | 3 | D Altchains | 0.0000 | 0.0000 |
| cosmos | ATOM | 3 | D Altchains | 0.3253 | 0.6962 |
| nem | XEM | 3 | D Altchains | 0.0000 | 0.0000 |
| maker | MKR | 6 | C Smart Token | 0.9549 | 0.2608 |
| ontology | ONT | 3 | D Altchains | 0.3497 | 0.5282 |
| crypto.comchain | CRO | 7 | C Utility Token | 0.0016 | 0.0057 |
| usdcoin | USDC | 5 | C Stable Token | 0.0000 | 0.0000 |
| zcash | ZEC | 2 | D Altcoins | 0.0003 | 0.0004 |
| vsystems | VSYS | 3 | D Altchains | 0.0355 | 0.0214 |
| dogecoin | DOGE | 2 | D Altcoins | 0.0000 | 0.0000 |
| vechain | VET | 3 | D Altchains | 0.1947 | 0.4352 |

Exhibit D.6: Table of white noise tests Panel B

| Asset | Ticker | class | Name of asset class | Portmanteau test for white noise (3 lags) | Breusch-Godfrey test (5lags) |
|---|---|---|---|---|---|
| decred | DCR | 2 | D Altcoins | 0.0001 | 0.0000 |
| basicattention | BAT | 7 | C Utility Token | 0.3367 | 0.1059 |
| btcgold | BTG | 2 | D Altcoins | 0.7944 | 0.2838 |
| huobitoken | HT | 7 | C Utility Token | 0.7326 | 0.4358 |
| qtum | QTUM | 3 | D Altchains | 0.0360 | 0.0974 |
| hedgetrade | HEDGE | 6 | C Smart Token | 0.0083 | 0.0104 |
| egretia | EGT | 6 | C Smart Token | 0.1809 | 0.1796 |
| trueusd | TUSD | 5 | C Stable Token | 0.0000 | 0.0000 |
| paxos | PAX | 5 | C Stable Token | 0.0006 | 0.0006 |
| omisego | OMG | 3 | D Altchains | 0.0420 | 0.0216 |
| kucoinshares | KCS | 7 | C Utility Token | 0.0012 | 0.0000 |
| ravencoin | RVN | 3 | D Altchains | 0.9652 | 0.2346 |
| lisk | LSK | 3 | D Altchains | 0.0000 | 0.0000 |
| bitcoindiamond | BCD | 2 | D Altcoins | 0.0007 | 0.0001 |
| nano | NANO | 2 | D Altcoins | 0.0023 | 0.0006 |
| bittorrent | BTT | 6 | C Smart Token | 0.0330 | 0.0188 |
| energi | NRG | 3 | D Altchains | 0.4013 | 0.1785 |
| educare | EKT | 6 | C Smart Token | 0.0109 | 0.0001 |
| waves | WAVES | 3 | D Altchains | 0.0803 | 0.0520 |
| holo | HOT | 6 | C Smart Token | 0.5930 | 0.0068 |
| lambda | LAMB | 6 | C Smart Token | 0.0029 | 0.0101 |
| hypercash | HC | 2 | D Altcoins | 0.2738 | 0.4302 |
| dai (sai) | SAI | 4 | D Stable Algorithmic | 0.0000 | 0.0000 |
| bitusd | BITUSD | 4 | D Stable Algorithmic | 0.0000 | 0.0000 |
| sbd | SBD | 4 | D Stable Algorithmic | 0.0000 | 0.0000 |
| bitshares | BTS | 6 | C Smart Token | 0.0000 | 0.0000 |
| Digix Gold token | DGX | 5 | C Stable Token | 0.0000 | 0.0000 |
| **Grand Total** | | | **Asset class** | | |
| ***D Bitcoin*** | | | ***D Bitcoin*** | 0 | 0 |
| ***D Altcoins*** | | | ***D Altcoins*** | 6 | 7 |
| ***D Altchains*** | | | ***D Altchains*** | 11 | 9 |
| ***D Stable Algorithmic*** | | | ***D Stable Algorithmic*** | 3 | 3 |
| ***C Stable Token*** | | | ***C Stable Token*** | 5 | 5 |
| ***C Utility Token*** | | | ***C Utility Token*** | 3 | 3 |
| ***C Smart Token*** | | | ***C Smart Token*** | 7 | 8 |

Exhibit D.7: Table of serially independent tests Panel A

| | | | | RUNTEST | | |
|---|---|---|---|---|---|---|
| Asset | Ticker | class | Name of asset class | Run test number of runs | Run test (z-stat) | Run test (p-value) |
| bitcoin | BTC | 1 | D Bitcoin | 1,163 | 1.18 | 0.2400 |
| ethereum | ETH | 3 | D Altchains | 758 | 1.64 | 0.1000 |
| ripple | XRP | 6 | C Smart Token | 1,082 | -0.26 | 0.8000 |
| bitcoincash | BCH | 2 | D Altcoins | 389 | 1.72 | 0.0900 |
| litecoin | LTC | 2 | D Altcoins | 974 | 2.53 | 0.0100 |
| BinanceCoin | BNB | 7 | C Utility Token | 381 | 0.92 | 0.3600 |
| tether | USDT | 5 | C Stable Token | 485 | -4.83 | 0.0000 |
| eos | EOS | 3 | D Altchains | 409 | 2.18 | 0.0300 |
| bitcoinsv | BSV | 2 | D Altcoins | 143 | 1.51 | 0.1300 |
| monero | XMR | 2 | D Altcoins | 993 | 3.01 | 0.0000 |
| stellar | XLM | 6 | C Smart Token | 981 | 3.04 | 0.0000 |
| tron | TRX | 3 | D Altchains | 361 | 1.42 | 0.1600 |
| cardano | ADA | 3 | D Altchains | 345 | 0.85 | 0.3900 |
| unus sed leo | LEO | 6 | C Smart Token | 34 | -0.42 | 0.6700 |
| dash | DASH | 2 | D Altcoins | 967 | 1.92 | 0.0600 |
| tezos | XTZ | 3 | D Altchains | 346 | 0.95 | 0.3400 |
| chainlink | LINK | 6 | C Smart Token | 346 | 0.53 | 0.6000 |
| neo | NEO | 3 | D Altchains | 544 | 1.01 | 0.3100 |
| iota | MIOTA | 3 | D Altchains | 449 | 4.36 | 0.0000 |
| ethclass | ETC | 3 | D Altchains | 587 | 2.33 | 0.0200 |
| cosmos | ATOM | 3 | D Altchains | 78 | 1.39 | 0.1600 |
| nem | XEM | 3 | D Altchains | 856 | 3.27 | 0.0000 |
| maker | MKR | 6 | C Smart Token | 318 | 0.00 | 1.0000 |
| ontology | ONT | 3 | D Altchains | 260 | 0.65 | 0.5100 |
| crypto.comchain | CRO | 7 | C Utility Token | 124 | 0.43 | 0.6700 |
| usdcoin | USDC | 5 | C Stable Token | 115 | 1.74 | 0.0800 |
| zcash | ZEC | 2 | D Altcoins | 511 | 0.77 | 0.4400 |
| vsystems | VSYS | 3 | D Altchains | 84 | 1.81 | 0.0700 |
| dogecoin | DOGE | 2 | D Altcoins | 1,067 | 2.48 | 0.0100 |
| vechain | VET | 3 | D Altchains | 206 | 2.60 | 0.0100 |

Exhibit D.8: Table of serially independent tests Panel B

| | | | | RUNTEST | | |
|---|---|---|---|---|---|---|
| **Asset** | **Ticker** | **class** | **Name of asset class** | **Run test number of runs** | **Run test (z-stat)** | **Run test (p-value)** |
| decred | DCR | 2 | D Altcoins | 674 | 2.31 | 0.0200 |
| basicattention | BAT | 7 | C Utility Token | 414 | 1.34 | 0.1800 |
| btcgold | BTG | 2 | D Altcoins | 348 | 1.99 | 0.0500 |
| huobitoken | HT | 7 | C Utility Token | 280 | 0.95 | 0.3400 |
| qtum | QTUM | 3 | D Altchains | 413 | 1.09 | 0.2800 |
| hedgetrade | HEDGE | 6 | C Smart Token | 71 | -0.55 | 0.5800 |
| egretia | EGT | 6 | C Smart Token | 202 | 0.46 | 0.6400 |
| trueusd | TUSD | 5 | C Stable Token | 208 | 0.84 | 0.4000 |
| paxos | PAX | 5 | C Stable Token | 109 | 0.18 | 0.8500 |
| omisego | OMG | 3 | D Altchains | 404 | 2.25 | 0.0200 |
| kucoinshares | KCS | 7 | C Utility Token | 331 | 0.80 | 0.9200 |
| ravencoin | RVN | 3 | D Altchains | 262 | 0.94 | 0.3500 |
| lisk | LSK | 3 | D Altchains | 647 | 2.51 | 0.0100 |
| bitcoindiamond | BCD | 2 | D Altcoins | 311 | 0.62 | 0.5300 |
| nano | NANO | 2 | D Altcoins | 469 | 2.66 | 0.0100 |
| bittorrent | BTT | 6 | C Smart Token | 87 | -0.32 | 0.7500 |
| energi | NRG | 3 | D Altchains | 186 | 1.65 | 0.1000 |
| educare | EKT | 6 | C Smart Token | 313 | 3.27 | 0.0000 |
| waves | WAVES | 3 | D Altchains | 608 | 1.85 | 0.0600 |
| holo | HOT | 6 | C Smart Token | 253 | 2.37 | 0.0200 |
| lambda | LAMB | 6 | C Smart Token | 101 | -0.62 | 0.5300 |
| hypercash | HC | 2 | D Altcoins | 371 | 1.36 | 0.1700 |
| dai (sai) | SAI | 4 | D Stable Algorithmic | 330 | 5.61 | 0.0000 |
| bitusd | BITUSD | 4 | D Stable Algorithmic | 1,023 | 8.35 | 0.0000 |
| sbd | SBD | 4 | D Stable Algorithmic | 613 | 3.77 | 0.0000 |
| bitshares | BTS | 6 | C Smart Token | 987 | 3.36 | 0.0000 |
| Digix Gold token | DGX | 5 | C Stable Token | 255 | 3.20 | 0.0000 |
| **Grand Total** | | | **Asset class** | | | |
| ***D Bitcoin*** | | | ***D Bitcoin*** | | | 0 |
| ***D Altcoins*** | | | ***D Altcoins*** | | | 5 |
| ***D Altchains*** | | | ***D Altchains*** | | | 7 |
| ***D Stable Algorithmic*** | | | ***D Stable Algorithmic*** | | | 3 |
| ***C Stable Token*** | | | ***C Stable Token*** | | | 2 |
| ***C Utility Token*** | | | ***C Utility Token*** | | | 0 |
| ***C Smart Token*** | | | ***C Smart Token*** | | | 4 |

Exhibit D.9: Table of time-varying volatility tests Panel A

| | | | | | | ARCH-M (QMLE) | | EGARCH | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Asset | Ticker | class | Name of asset class | Arch LM test (p-value) | Lag for which ArchLM<0,05 | coeff (M) | model | coeff (lev) | p-value | coeff (symm.) | p-value |
| bitcoin | BTC | 1 | D Bitcoin | 0.0000 | | 1.191* | garch(1/1) | -0.0020 | 0.9280 | 0.2919 | 0.0000 |
| ethereum | ETH | 3 | D Altchains | 0.0281 | | -2.117964*** | garch(1/1) | 0.0194 | 0.4470 | 0.3058 | 0.0000 |
| ripple | XRP | 6 | C Smart Token | 0.0003 | | 0.4472847*** | garch(1/1) | 0.0775 | 0.1910 | 0.5872 | 0.0000 |
| bitcoincash | BCH | 2 | D Altcoins | 0.0000 | | 1.929006 | garch(1/1) | 0.0558 | 0.1660 | 0.1701 | 0.0010 |
| litecoin | LTC | 2 | D Altcoins | 0.0000 | | 3.106357** | garch(1/3) | 0.0732 | 0.1170 | 0.2273 | 0.0000 |
| BinanceCoin | BNB | 7 | C Utility Token | 0.0000 | | -0.2013731 | garch(1/1) | 0.0362 | 0.3650 | 0.3234 | 0.0050 |
| tether | USDT | 5 | C Stable Token | 0.0000 | | -8.029627*** | | | | | |
| eos | EOS | 3 | D Altchains | 0.0304 | 8 | 347.2255** | garch(1/1) | 0.0114 | 0.6590 | 0.0169 | 0.8560 |
| bitcoinsv | BSV | 2 | D Altcoins | 0.5089 | 2 | 0.1173941** | | | | | |
| monero | XMR | 2 | D Altcoins | 0.0000 | | 2.151328** | garch(1/1) | 0.0954 | 0.0020 | 0.2143 | 0.0040 |
| stellar | XLM | 6 | C Smart Token | 0.0000 | | 0.1119292 | garch(1/1) | 0.1050 | 0.0660 | 0.3992 | 0.0050 |
| tron | TRX | 3 | D Altchains | 0.0978 | 2 | -0.7421185*** | | | | | |
| cardano | ADA | 3 | D Altchains | 0.0141 | | 1.444562*** | garch(1/1) | 0.0919 | 0.3050 | 0.3133 | 0.0910 |
| unus sed leo | LEO | 6 | C Smart Token | 0.0129 | >10 | 3.2236 | garch(1/2) | -0.0393 | 0.6780 | 0.0116 | 0.8300 |
| dash | DASH | 2 | D Altcoins | 0.0000 | | 1.594237* | garch(1/1) | 0.0083 | 0.8420 | 0.4103 | 0.0000 |
| tezos | XTZ | 3 | D Altchains | 0.0003 | | -0.3540804 | garch(1/1) | 0.1051 | 0.0930 | 0.4343 | 0.0000 |
| chainlink | LINK | 6 | C Smart Token | 0.0191 | >10 | -0.7442187 | garch(1/1) | 0.0235 | 0.3820 | 0.1479 | 0.0000 |
| neo | NEO | 3 | D Altchains | 0.0003 | | -0.0474542 | garch(1/1) | 0.0440 | 0.1090 | 0.1585 | 0.1670 |
| iota | MIOTA | 3 | D Altchains | 0.0000 | | 2.576963 | garch(1/1) | 0.0084 | 0.7950 | 0.2549 | 0.0000 |
| ethclass | ETC | 3 | D Altchains | 0.4403 | 3 | -0.0244182** | | | | | |
| cosmos | ATOM | 3 | D Altchains | 0.7598 | | n/a | | | | | |
| nem | XEM | 3 | D Altchains | 0.0287 | >10 | 0.0960797 | garch(1/1) | -0.1090 | 0.3910 | 0.7878 | 0.0010 |
| maker | MKR | 6 | C Smart Token | 0.0386 | | 4.056881** | garch(1/1) | -0.0008 | 0.9910 | 0.2438 | 0.2180 |
| ontology | ONT | 3 | D Altchains | 0.0000 | | 0.552298 | garch(1/1) | 0.1203 | 0.0970 | 0.3997 | 0.0000 |
| crypto.comchain | CRO | 7 | C Utility Token | 0.9897 | | 55.52671 | | | | | |
| usdcoin | USDC | 5 | C Stable Token | 0.0000 | | -77.84921*** | garch(1/1) | 0.0776 | 0.2780 | 0.1385 | 0.0000 |
| zcash | ZEC | 2 | D Altcoins | 0.0000 | | 0.7954438** | garch(1/1) | -0.0225 | 0.7090 | 0.4266 | 0.0020 |
| vsystems | VSYS | 3 | D Altchains | 0.9449 | | n/a | | | | | |
| dogecoin | DOGE | 2 | D Altcoins | 0.0000 | | -0.328809** | garch(1/1) | 0.0656 | 0.0900 | 0.3886 | 0.0000 |
| vechain | VET | 3 | D Altchains | 0.0000 | | 3.029068 | garch(1/1) | -0.0797 | 0.2100 | 0.2114 | 0.1660 |

*Notes: (*) significant at 10 %; (**) significant at 5%; (***) significant at 1%.*

Exhibit D.10: Table of time-varying volatility tests Panel B

| Asset | Ticker | class | Name of asset class | Arch LM test (p-value) | Lag for which ArchLM<0,05 | ARCH-M (QMLE) coeff (M) | model | EGARCH coeff (lev) | p-value | coeff (symm.) | p-value |
|---|---|---|---|---|---|---|---|---|---|---|---|
| decred | DCR | 2 | D Altcoins | 0.0000 | | 0.4453634 | garch(1/1) | 0.0872 | 0.0050 | -0.0039 | 0.9460 |
| basicattention | BAT | 7 | C Utility Token | 0.4316 | 5 | 2.824548* | | | | | |
| btcgold | BTG | 2 | D Altcoins | 0.0003 | | 0.4984024 | garch(1/1) | 0.0048 | 0.8420 | 0.1365 | 0.1960 |
| huobitoken | HT | 7 | C Utility Token | 0.0000 | | 4.628226 | garch(1/1) | 0.0567 | 0.0770 | 0.1364 | 0.0040 |
| qtum | QTUM | 3 | D Altchains | 0.0000 | | 1.622832 | garch(1/1) | 0.0199 | 0.6010 | 0.2014 | 0.0080 |
| hedgetrade | HEDGE | 6 | C Smart Token | 0.2271 | 3 | 0.2925459 | | | | | |
| egretia | EGT | 6 | C Smart Token | 0.1362 | 7 | 1.978218 | | | | | |
| trueusd | TUSD | 5 | C Stable Token | 0.0000 | | 2.972331* | garch(1/1) | 0.0484 | 0.2640 | 0.0603 | 0.0810 |
| paxos | PAX | 5 | C Stable Token | 0.0000 | | -25.35137 | garch(1/1) | 0.0865 | 0.2210 | 0.5184 | 0.0000 |
| omisego | OMG | 3 | D Altchains | 0.0001 | | 1.77854** | garch(1/1) | 0.0024 | 0.9310 | 0.2257 | 0.0000 |
| kucoinshares | KCS | 7 | C Utility Token | 0.0677 | 2 | -0.8637519* | | | | | |
| ravencoin | RVN | 3 | D Altchains | 0.0010 | | -0.12661 | garch(1/1) | 0.2454 | 0.0010 | 0.2609 | 0.0200 |
| lisk | LSK | 3 | D Altchains | 0.0000 | | -0.331498** | garch(1/1) | -0.0272 | 0.3600 | 0.2942 | 0.0000 |
| bitcoindiamond | BCD | 2 | D Altcoins | 0.9550 | | -60.14836 | | | | | |
| nano | NANO | 2 | D Altcoins | 0.0210 | | 1.297438*** | garch(1/1) | 0.0755 | 0.0880 | 0.2193 | 0.1170 |
| bittorrent | BTT | 6 | C Smart Token | 0.0000 | | 3.856643 | garch(1/1) | -0.0297 | 0.8340 | 0.4521 | 0.0470 |
| energi | NRG | 3 | D Altchains | 0.1846 | | 1.70409 | | | | | |
| educare | EKT | 6 | C Smart Token | 0.0517 | | 0.1057285 | | | | | |
| waves | WAVES | 3 | D Altchains | 0.0000 | | 1.324283** | garch(1/1) | -0.0271 | 0.4000 | 0.3416 | 0.0000 |
| holo | HOT | 6 | C Smart Token | 0.0000 | | 2.58733** | garch(1/2) | 0.2249 | 0.0200 | 0.2822 | 0.0010 |
| lambda | LAMB | 6 | C Smart Token | 0.1112 | 2 | -0.31741* | | | | | |
| hypercash | HC | 2 | D Altcoins | 0.0019 | | 0.2129776 | garch(1/1) | -0.0132 | 0.8180 | 0.3208 | 0.0060 |
| dai (sai) | SAI | 4 | D Stable Algorithmic | 0.2142 | | 0.2833245 | | | | | |
| bitusd | BITUSD | 4 | D Stable Algorithmic | 0.0130 | | 0.001972 | | -0.0892 | 0.6090 | 1.3497 | 0.0000 |
| sbd | SBD | 4 | D Stable Algorithmic | 0.0604 | | -1.454345 | | | | | |
| bitshares | BTS | 6 | C Smart Token | 0.0000 | | -0.4971085 | garch(1/2) | 0.0714 | 0.0320 | 0.2725 | 0.0000 |
| Digix Gold token | DGX | 5 | C Stable Token | 0.0024 | >10 | -1.858239 | garch(1/1) | 0.0500 | 0.3960 | 0.2869 | 0.0550 |
| **Grand Total** | | | **Asset class** | | | | | | | | |
| ***D Bitcoin*** | | | ***D Bitcoin*** | 1 | | 0 | | | 0 | | 1 |
| ***D Altcoins*** | | | ***D Altcoins*** | 10 | | 7 | | | 2 | | 7 |
| ***D Altchains*** | | | ***D Altchains*** | 14 | | 8 | | | 1 | | 10 |
| ***D Stable Algorithmic*** | | | ***D Stable Algorithmic*** | 1 | | 0 | | | 0 | | 1 |
| ***C Stable Token*** | | | ***C Stable Token*** | 5 | | 3 | | | 0 | | 2 |
| ***C Utility Token*** | | | ***C Utility Token*** | 2 | | 2 | | | 0 | | 2 |
| ***C Smart Token*** | | | ***C Smart Token*** | 8 | | 4 | | | 2 | | 6 |

*Notes: (*) significant at 10 %; (**) significant at 5%; (***) significant at 1%.*

## Exhibit D.11: Table of the day-of-the-week tests Panel A

| | | | | | coeff. | coeff. | coeff. | coeff. | coeff. | coeff. | coeff. | p-value | p-value | p-value | p-value | p-value | p-value | p-value | coeff. | coeff. | coeff. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Asset** | **Ticker** | **class** | **Name of asset class** | **model** | **mon** | **tue** | **wed** | **thu** | **fri** | **sat** | **sun** | **mon** | **tue** | **wed** | **thu** | **fri** | **sat** | **sun** | **arch** | **garch(1)** | **garch(2)** |
| bitcoin | BTC | 1 | D Bitcoin | garch(1,1) | 0.0021 | 0.0042 | -0.0024 | -0.0001 | 0.0034 | 0.0028 | -0.0001 | 0.2860 | 0.0630 | 0.2130 | 0.9570 | 0.0580 | 0.1380 | 0.9530 | 0.1411 | 0.8362 | |
| ethereum | ETH | 3 | D Altchains | garch(1,1) | -0.0016 | 0.0101 | -0.0056 | -0.0054 | 0.0093 | 0.0051 | 0.0000 | 0.6560 | 0.0160 | 0.1590 | 0.2380 | 0.0600 | 0.2080 | 0.9900 | 0.1968 | 0.7450 | |
| ripple | XRP | 6 | C Smart Token | garch(1,3) | -0.0030 | 0.0046 | -0.0081 | -0.0057 | 0.0042 | -0.0021 | -0.0041 | 0.3810 | 0.3530 | 0.2770 | 0.1870 | 0.2120 | 0.3920 | 0.2000 | 0.2627 | 0.7300 | |
| bitcoincash | BCH | 2 | D Altcoins | garch(1,1/2) | -0.0024 | 0.0021 | -0.0078 | -0.0194 | 0.0133 | 0.0141 | -0.0049 | 0.7530 | 0.8090 | 0.3250 | 0.0550 | 0.0440 | 0.0200 | 0.4470 | 0.1583 | 0.3054 | 0.4423 |
| litecoin | LTC | 2 | D Altcoins | garch(1,1) | -0.0044 | 0.0035 | -0.0057 | 0.0010 | 0.0053 | 0.0016 | -0.0009 | 0.1030 | 0.3200 | 0.0570 | 0.7990 | 0.1180 | 0.5890 | 0.7340 | 0.0697 | 0.8745 | |
| BinanceCoin | BNB | 7 | C Utility Token | garch(1,1) | -0.0011 | 0.0064 | -0.0022 | 0.0003 | 0.0193 | 0.0064 | -0.0084 | 0.8650 | 0.3060 | 0.6780 | 0.9560 | 0.0020 | 0.1900 | 0.1020 | 0.1592 | 0.8357 | |
| tether | USDT | 5 | C Stable Token | ols (vce) | 0.0001 | 0.0000 | 0.0002 | 0.0000 | 0.0007 | 0.0002 | -0.0001 | 0.7280 | 0.9600 | 0.7580 | 0.9510 | 0.1020 | 0.7030 | 0.7340 | | | |
| eos | EOS | 3 | D Altchains | garch(1,1) | -0.0004 | 0.0063 | 0.0092 | -0.0140 | 0.0110 | 0.0073 | 0.0010 | 0.9670 | 0.4810 | 0.3080 | 0.0830 | 0.1590 | 0.2770 | 0.9200 | 0.0024 | 0.9934 | |
| bitcoinsv | BSV | 2 | D Altcoins | ols (vce) | -0.0035 | 0.0297 | 0.0216 | -0.0320 | 0.0178 | 0.0123 | 0.0091 | 0.8070 | 0.3640 | 0.2840 | 0.1030 | 0.1890 | 0.2320 | 0.6120 | | | |
| monero | XMR | 2 | D Altcoins | garch(1,1) | -0.0006 | 0.0024 | -0.0003 | -0.0043 | 0.0016 | 0.0034 | -0.0010 | 0.8810 | 0.5670 | 0.9370 | 0.3070 | 0.6780 | 0.5030 | 0.8190 | 0.1289 | 0.8205 | |
| stellar | XLM | 6 | C Smart Token | garch(1,1) | -0.0071 | -0.0023 | 0.0055 | -0.0027 | -0.0050 | -0.0020 | 0.0073 | 0.1740 | 0.6760 | 0.2590 | 0.5200 | 0.1410 | 0.6260 | 0.1550 | 0.2502 | 0.7372 | |
| tron | TRX | 3 | D Altchains | ols (vce) | 0.0004 | 0.0063 | 0.0297 | 0.0019 | 0.0048 | 0.0196 | 0.0009 | 0.9690 | 0.5710 | 0.0630 | 0.9010 | 0.5580 | 0.1070 | 0.9370 | | | |
| cardano | ADA | 3 | D Altchains | garch(1,1) | -0.0059 | -0.0028 | -0.0069 | -0.0158 | 0.0094 | 0.0100 | -0.0078 | 0.4390 | 0.6870 | 0.3880 | 0.0380 | 0.1540 | 0.1200 | 0.2260 | 0.1684 | 0.8243 | |
| unus sed leo | LEO | 6 | C Smart Token | garch(1,1) | 0.0231 | -0.0193 | 0.0038 | -0.0007 | -0.0135 | 0.0012 | -0.0032 | 0.1080 | 0.0750 | 0.7150 | 0.9520 | 0.1820 | 0.8780 | 0.7160 | 0.2652 | 0.6817 | |
| dash | DASH | 2 | D Altcoins | garch(1,1) | -0.0006 | 0.00396 | 0.00063 | 0.00195 | 0.00601 | 0.00297 | 0.00273 | 0.86500 | 0.29600 | 0.87100 | 0.65000 | 0.05700 | 0.61100 | 0.44500 | 0.6968 | 0.2726 | |
| tezos | XTZ | 3 | D Altchains | garch(1,1) | -0.0104 | 0.0006 | -0.0014 | -0.0006 | 0.0052 | 0.0077 | 0.0004 | 0.1770 | 0.9360 | 0.8410 | 0.9230 | 0.3570 | 0.2160 | 0.9510 | 0.3529 | 0.4871 | |
| chainlink | LINK | 6 | C Smart Token | garch(1,1) | -0.0010 | 0.0200 | -0.0032 | 0.0038 | 0.0098 | 0.0123 | -0.0026 | 0.9020 | 0.0220 | 0.7120 | 0.6610 | 0.1650 | 0.0860 | 0.6960 | 0.0726 | 0.9182 | |
| neo | NEO | 3 | D Altchains | garch(1,1) | 0.0044 | 0.0027 | -0.0009 | -0.0118 | 0.0053 | 0.0090 | 0.0019 | 0.5260 | 0.6860 | 0.9150 | 0.1110 | 0.5680 | 0.1940 | 0.7930 | 0.0690 | 0.9242 | |
| iota | MIOTA | 3 | D Altchains | garch(1,1) | -0.0011 | 0.0012 | -0.0021 | -0.0117 | 0.0042 | 0.0054 | -0.0102 | 0.8720 | 0.8380 | 0.7440 | 0.1140 | 0.4270 | 0.2370 | 0.0510 | 0.1176 | 0.8645 | |
| ethclass | ETC | 3 | D Altchains | ols (vce) | -0.0003 | 0.0258 | -0.0018 | -0.0029 | 0.0105 | 0.0030 | 0.0064 | 0.9590 | 0.2210 | 0.7940 | 0.6200 | 0.0560 | 0.5150 | 0.2460 | | | |
| cosmos | ATOM | 3 | D Altchains | ols (vce) | 0.0032 | -0.0403 | -0.0027 | -0.0208 | 0.0439 | 0.0099 | 0.0019 | 0.4900 | 0.8580 | 0.2630 | 0.8980 | 0.7260 | 0.2920 | 0.6010 | | | |
| nem | XEM | 3 | D Altchains | garch(6,1) | 0.0056 | -0.0011 | 0.0123 | -0.0009 | 0.0031 | -0.0193 | -0.0031 | 0.4900 | 0.8580 | 0.2630 | 0.8980 | 0.7260 | 0.2920 | 0.6010 | 0.2219 | 0.7718 | |
| maker | MKR | 6 | C Smart Token | garch(1,1) | -0.0036 | 0.0045 | -0.0055 | -0.0028 | 0.0074 | 0.0054 | -0.0033 | 0.5850 | 0.4720 | 0.4130 | 0.6570 | 0.1720 | 0.2320 | 0.5370 | 0.0898 | 0.8807 | |
| ontology | ONT | 3 | D Altchains | garch(1,1) | -0.0078 | 0.0000 | -0.0016 | -0.0224 | 0.0044 | 0.0104 | -0.0025 | 0.3400 | 0.9970 | 0.8500 | 0.0160 | 0.6180 | 0.1550 | 0.7070 | 0.2650 | 0.5826 | |
| crypto.comchain | CRO | 7 | C Utility Token | ols (vce) | -0.0093 | -0.0194 | 0.0002 | 0.0430 | 0.0138 | 0.0179 | 0.0198 | 0.2710 | 0.0450 | 0.9890 | 0.3140 | 0.4060 | 0.3660 | 0.3690 | | | |
| usdcoin | USDC | 5 | C Stable Token | garch(1,1) | 0.0005 | -0.0001 | -0.0017 | 0.0009 | 0.0004 | -0.0014 | 0.0016 | 0.4620 | 0.8760 | 0.2140 | 0.3730 | 0.5220 | 0.0150 | 0.0140 | 0.3861 | 0.3880 | |
| zcash | ZEC | 2 | D Altcoins | garch(1,1) | -0.0009 | 0.0086 | -0.0036 | -0.0067 | 0.0041 | 0.0061 | -0.0159 | 0.8550 | 0.0850 | 0.4700 | 0.2390 | 0.4240 | 0.1970 | 0.0210 | 0.2478 | 0.7646 | |
| vsystems | VSYS | 3 | D Altchains | ols (vce) | -0.0056 | 0.0556 | 0.0164 | 0.0056 | 0.0283 | 0.0211 | 0.0019 | 0.6470 | 0.0160 | 0.5640 | 0.7360 | 0.1110 | 0.1000 | 0.8970 | | | |
| dogecoin | DOGE | 2 | D Altcoins | garch(1,2) | 0.0019 | -0.0041 | -0.0044 | -0.0013 | 0.0040 | -0.0032 | -0.0049 | 0.5630 | 0.1730 | 0.0760 | 0.6250 | 0.1070 | 0.2430 | 0.1490 | 0.2758 | 0.6997 | 0.0598 |
| vechain | VET | 3 | D Altchains | garch(1,1) | -0.0057 | 0.0173 | 0.0003 | -0.0097 | 0.0123 | -0.0011 | -0.0134 | 0.5470 | 0.0630 | 0.9660 | 0.2200 | 0.0450 | 0.8440 | 0.0690 | 0.1392 | 0.7713 | |

Exhibit D.12: Table of the day-of-the-week tests Panel B

| Asset | Ticker | class | Name of asset class | model | mon coeff. | tue coeff. | wed coeff. | thu coeff. | fri coeff. | sat coeff. | sun coeff. | mon p-value | tue p-value | wed p-value | thu p-value | fri p-value | sat p-value | sun p-value | arch coeff. | garch(1) coeff. | garch(2) coeff. | arch(1) p-value | garch(1) p-value | garch(2) p-value |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| decred | DCR | 2 | D Altcoins | garch(1,1) | 0.0011 | 0.0017 | 0.0094 | -0.0043 | 0.0103 | 0.0072 | -0.0016 | 0.8370 | 0.7680 | 0.0790 | 0.3610 | 0.0270 | 0.0890 | 0.7250 | 0.0286 | 0.9631 | | 0.0220 | 0.0000 | |
| basicattention | BAT | 7 | C Utility Token | ols (vce) | 0.0053 | 0.0019 | -0.0035 | 0.0012 | 0.0113 | 0.0108 | -0.0025 | 0.4870 | 0.7960 | 0.6530 | 0.8900 | 0.1450 | 0.1010 | 0.7730 | | | | | | |
| btcgold | BTG | 2 | D Altcoins | garch(1,1) | -0.0038 | -0.0021 | 0.0013 | -0.0100 | 0.0122 | 0.0045 | -0.0037 | 0.5680 | 0.7950 | 0.7990 | 0.1030 | 0.0910 | 0.3670 | 0.5080 | 0.0349 | 0.9544 | | 0.2070 | 0.0000 | |
| huobitoken | HT | 7 | C Utility Token | garch(1,1) | 0.0013 | 0.0084 | -0.0031 | -0.0059 | 0.0135 | 0.0036 | 0.0009 | 0.8560 | 0.3370 | 0.6520 | 0.3510 | 0.0060 | 0.4040 | 0.8670 | 0.1505 | -0.3364 | | 0.0010 | 0.2490 | |
| qtum | QTUM | 3 | D Altchains | garch(1,1) | 0.0017 | 0.0032 | -0.0088 | -0.0011 | 0.0076 | 0.0067 | -0.0030 | 0.8410 | 0.6480 | 0.2760 | 0.8950 | 0.2220 | 0.3330 | 0.5920 | 0.0939 | 0.8882 | | 0.0240 | 0.0000 | |
| hedgetrade | HEDGE | 6 | C Smart Token | ols (vce) | -0.0019 | 0.0479 | 0.0243 | 0.0223 | 0.0045 | 0.0097 | 0.0218 | 0.9590 | 0.0260 | 0.1690 | 0.3300 | 0.8550 | 0.6110 | 0.1930 | | | | | | |
| egretia | EGT | 6 | C Smart Token | ols (vce) | 0.0139 | 0.0097 | 0.0208 | -0.0123 | 0.0145 | 0.0157 | 0.0057 | 0.3590 | 0.5360 | 0.1310 | 0.3310 | 0.3090 | 0.1550 | 0.5080 | | | | | | |
| trueusd | TUSD | 5 | C Stable Token | garch(1,1) | 0.0002 | -0.0002 | 0.0002 | 0.0001 | -0.0001 | -0.0002 | 0.0022 | 0.8040 | 0.7560 | 0.7430 | 0.9480 | 0.8100 | 0.6880 | 0.0150 | 0.6910 | 0.1928 | | 0.0250 | 0.1450 | |
| paxos | PAX | 5 | C Stable Token | garch(1,1) | 0.0008 | -0.0005 | 0.0008 | 0.0005 | -0.0001 | -0.0001 | 0.0001 | 0.2000 | 0.5270 | 0.1460 | 0.4030 | 0.7270 | 0.8920 | 0.8760 | 0.2937 | 0.6798 | | 0.0010 | 0.0000 | |
| omisego | OMG | 3 | D Altchains | garch(1,1) | -0.0051 | 0.0008 | -0.0025 | -0.0114 | 0.0052 | 0.0076 | -0.0029 | 0.4410 | 0.8950 | 0.7220 | 0.0900 | 0.3760 | 0.1630 | 0.5700 | 0.1082 | 0.8719 | | 0.0020 | 0.0000 | |
| kucoinshares | KCS | 7 | C Utility Token | ols (vce) | 0.0017 | 0.0056 | 0.0070 | -0.0080 | 0.0103 | 0.0207 | -0.0032 | 0.8610 | 0.6690 | 0.4550 | 0.2970 | 0.1470 | 0.0640 | 0.6990 | | | | | | |
| ravencoin | RVN | 3 | D Altchains | garch(1,1) | -0.0203 | -0.0058 | 0.0043 | -0.0038 | 0.0030 | 0.0061 | -0.0155 | 0.1250 | 0.6430 | 0.7370 | 0.7050 | 0.6670 | 0.4750 | 0.1510 | 0.5278 | 0.0725 | | 0.0760 | 0.6180 | |
| lisk | LSK | 3 | D Altchains | garch(1,1) | -0.0009 | 0.0000 | -0.0015 | -0.0055 | 0.0001 | 0.0032 | 0.0017 | 0.8580 | 0.9970 | 0.7370 | 0.3190 | 0.9880 | 0.4070 | 0.6960 | 0.1654 | 0.8332 | | 0.0000 | 0.0000 | |
| bitcoindiamond | BCD | 2 | D Altcoins | ols (vce) | 0.0017 | 0.0056 | 0.0070 | -0.0080 | 0.0103 | 0.0207 | -0.0032 | 0.8610 | 0.6690 | 0.4550 | 0.2970 | 0.1470 | 0.0640 | 0.6990 | | | | | | |
| nano | NANO | 2 | D Altcoins | garch(3,1) | -0.0055 | 0.0074 | 0.0077 | -0.0080 | 0.0124 | -0.0007 | 0.0015 | 0.4570 | 0.3900 | 0.3430 | 0.3450 | 0.1240 | 0.8990 | 0.8490 | 0.0643 | 0.9379 | | 0.0730 | 0.0000 | |
| bittorrent | BTT | 6 | C Smart Token | garch(1,1) | -0.0106 | 0.0014 | 0.0053 | -0.0218 | 0.0069 | 0.0090 | 0.0157 | 0.2430 | 0.8820 | 0.5470 | 0.0060 | 0.4310 | 0.4550 | 0.1580 | 0.2957 | 0.6996 | | 0.1130 | 0.0000 | |
| energi | NRG | 3 | D Altchains | ols (vce) | 0.0166 | 0.0052 | 0.0123 | 0.0131 | 0.0241 | 0.0097 | 0.0015 | 0.2650 | 0.6490 | 0.3400 | 0.4170 | 0.0360 | 0.4330 | 0.9100 | | | | | | |
| educare | EKT | 6 | C Smart Token | ols (vce) | -0.0016 | 0.0013 | 0.0130 | 0.0006 | 0.0133 | 0.0098 | 0.0103 | 0.8830 | 0.9260 | 0.2360 | 0.9530 | 0.2220 | 0.6010 | 0.5470 | | | | | | |
| waves | WAVES | 3 | D Altchains | garch(1,1) | 0.0035 | -0.0041 | 0.0007 | -0.0114 | 0.0037 | 0.0051 | -0.0008 | 0.4920 | 0.4510 | 0.9050 | 0.0230 | 0.3920 | 0.2320 | 0.8650 | 0.2132 | 0.7593 | | 0.0020 | 0.0000 | |
| holo | HOT | 6 | C Smart Token | garch(1,2) | 0.0015 | -0.0006 | -0.0009 | -0.0179 | 0.0049 | 0.0067 | -0.0124 | 0.8800 | 0.9530 | 0.9140 | 0.0370 | 0.4970 | 0.4450 | 0.1750 | 0.2031 | 0.7591 | | 0.0020 | 0.0000 | |
| lambda | LAMB | 6 | C Smart Token | ols (vce) | 0.0248 | 0.0414 | 0.0273 | 0.0003 | -0.0006 | -0.0031 | 0.0708 | 0.1300 | 0.0560 | 0.2250 | 0.9810 | 0.9670 | 0.8180 | 0.0540 | | | | | | |
| hypercash | HC | 2 | D Altcoins | garch(1,1) | -0.0074 | 0.0073 | -0.0128 | -0.0105 | 0.0136 | 0.0150 | -0.0030 | 0.3970 | 0.4150 | 0.1980 | 0.2380 | 0.0660 | 0.0250 | 0.6870 | 0.2346 | 0.7377 | | 0.0290 | 0.0000 | |
| dai (sai) | SAI | 4 | D Stable Algorithmic | ols (vce) | -0.0004 | 0.0013 | -0.0001 | 0.0006 | 0.0012 | 0.0039 | -0.0006 | 0.7760 | 0.3820 | 0.9330 | 0.7370 | 0.5730 | 0.3120 | 0.6860 | | | | | | |
| bitusd | BITUSD | 4 | D Stable Algorithmic | ols (vce) | 0.0063 | -0.0102 | 0.0317 | -0.0104 | 0.0359 | -0.0066 | 0.0110 | 0.2150 | 0.0290 | 0.0870 | 0.0830 | 0.1030 | 0.1740 | 0.3920 | | | | | | |
| sbd | SBD | 4 | D Stable Algorithmic | ols (vce) | 0.0034 | -0.0010 | 0.0219 | -0.0055 | 0.0012 | 0.0111 | -0.0052 | 0.5050 | 0.8670 | 0.2970 | 0.5770 | 0.8290 | 0.0930 | 0.2020 | | | | | | |
| bitshares | BTS | 6 | C Smart Token | garch(1,1) | 0.0014 | -0.0026 | -0.0047 | -0.0046 | 0.0028 | 0.0080 | -0.0070 | 0.7340 | 0.5180 | 0.2830 | 0.3100 | 0.4870 | 0.1020 | 0.0800 | 0.1242 | 0.8566 | | 0.0430 | 0.0000 | |
| Digix Gold token | DGX | 5 | C Stable Token | garch(1,5) | -0.0047 | 0.0078 | -0.0070 | -0.0024 | 0.0080 | -0.0010 | 0.0121 | 0.2550 | 0.2010 | 0.2660 | 0.6460 | 0.0480 | 0.7480 | 0.0150 | 0.7266 | 0.0915 | | 0.0720 | 0.7110 | |

| Grand Total | Asset class | mon | tue | wed | thu | fri | sat | sun |
|---|---|---|---|---|---|---|---|---|
| ***D Bitcoin*** | ***D Bitcoin*** | 0 | 1 | 0 | 0 | 1 | 0 | 0 |
| ***D Altcoins*** | ***D Altcoins*** | 0 | 1 | 3 | 1 | 5 | 4 | 1 |
| ***D Altchains*** | ***D Altchains*** | 0 | 3 | 1 | 5 | 4 | 0 | 2 |
| ***D Stable Algorithmic*** | ***D Stable Algorithmic*** | 0 | 1 | 1 | 1 | 0 | 1 | 0 |
| ***C Stable Token*** | ***C Stable Token*** | 0 | 0 | 0 | 0 | 1 | 1 | 3 |
| ***C Utility Token*** | ***C Utility Token*** | 0 | 1 | 0 | 0 | 2 | 1 | 0 |
| ***C Smart Token*** | ***C Smart Token*** | 0 | 4 | 0 | 2 | 0 | 1 | 2 |

## Exhibit D.13: Table of regime switching tests Panel A

| | | | | coefficients | | volatility | | transition probabilities | | duration | | coefficients p-value | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Asset** | **Ticker** | **class** | **Name of asset class** | **mean.s1** | **mean.s2** | **stdev.s1** | **stdev.s2** | **p11** | **p21** | **d1** | **d2** | **1** | **mean.s2** |
| bitcoin | BTC | 1 | D Bitcoin | 0.0021177*** | 0.0036 | 0.017 | 0.066 | 91% | 13% | 12 | 8 | 0.0000 | 0.1200 |
| ethereum | ETH | 3 | D Altchains | -0.0022981* | 0.0195994*** | 0.030 | 0.110 | 88% | 22% | 9 | 4 | 0.0600 | 0.0010 |
| ripple | XRP | 6 | C Smart Token | -0.0004 | 0.5183108*** | 0.0674 | | 99% | 77% | 131 | 1 | 0.8180 | 0.0020 |
| bitcoincash | BCH | 2 | D Altcoins | -0.0068027*** | 0.0365392 | 0.045 | 0.167 | 89% | 41% | 9 | 2 | 0.0030 | 0.1670 |
| litecoin | LTC | 2 | D Altcoins | -0.0015728** | 0.0097848** | 0.020 | 0.095 | 88% | 19% | 9 | 5 | 0.0160 | 0.0220 |
| BinanceCoin | BNB | 7 | C Utility Token | 0.0012371 | 0.0546073 | 0.049 | 0.192 | 97% | 13% | 39 | 8 | 0.6440 | 0.2350 |
| tether | USDT | 5 | C Stable Token | 0.0003328 | 0.0000*** | 0.009 | 0.000 | 75% | 18% | 4 | 6 | 0.3630 | 0.0000 |
| eos | EOS | 3 | D Altchains | -0.0043519** | 0.0498982 | 0.049 | 0.211 | 93% | 32% | 13 | 3 | 0.0450 | 0.1910 |
| bitcoinsv | BSV | 2 | D Altcoins | -0.0061078** | 0.045167 | 0.033 | 0.216 | 89% | 29% | 9 | 3 | 0.0240 | 0.1590 |
| monero | XMR | 2 | D Altcoins | -0.0019952 | 0.0122485** | 0.035 | 0.101 | 91% | 12% | 12 | 8 | 0.1180 | 0.0190 |
| stellar | XLM | 6 | C Smart Token | -0.0051257*** | 0.0370731*** | 0.037 | 0.159 | 94% | 19% | 17 | 5 | 0.0000 | 0.0030 |
| tron | TRX | 3 | D Altchains | -0.0014609 | 0.0820105* | 0.061 | 0.291 | 99% | 7% | 88 | 14 | 0.5950 | 0.0500 |
| cardano | ADA | 3 | D Altchains | -0.0045923* | 0.2240331*** | 0.059 | 0.322 | 98% | 45% | 47 | 2 | 0.0640 | 0.0080 |
| unus sed leo | LEO | 6 | C Smart Token | -0.0067997 | 0.0286126** | 0.030 | 0.056 | 98% | 3% | 60 | 40 | 0.1020 | 0.0120 |
| dash | DASH | 2 | D Altcoins | -0.0026874** | 0.0193288* | 0.033 | 0.117 | 93% | 19% | 14 | 5 | 0.0220 | 0.0500 |
| tezos | XTZ | 3 | D Altchains | -0.004418* | 0.0276233 | 0.050 | 0.138 | 94% | 19% | 16 | 5 | 0.0970 | 0.1780 |
| chainlink | LINK | 6 | C Smart Token | -0.0040711 | 0.0367617* | 0.056 | 0.143 | 91% | 22% | 12 | 5 | 0.1960 | 0.0670 |
| neo | NEO | 3 | D Altchains | -0.0037578* | 0.1254392*** | 0.058 | 0.317 | 96% | 34% | 26 | 3 | 0.0890 | 0.0070 |
| iota | MIOTA | 3 | D Altchains | -0.0057652*** | 0.0202734* | 0.048 | 0.128 | 96% | 10% | 24 | 10 | 0.0090 | 0.0800 |
| ethclass | ETC | 3 | D Altchains | | | | | | | | | | |
| cosmos | ATOM | 3 | D Altchains | -0.002079 | 0.0023544 | 0.042 | 0.125 | 89% | 18% | 9 | 5 | 0.6700 | 0.8930 |
| nem | XEM | 3 | D Altchains | -0.0024148 | 0.0521657* | 0.049 | 0.201 | 94% | 30% | 16 | 3 | 0.1780 | 0.0590 |
| maker | MKR | 6 | C Smart Token | -0.0004123 | 0.0249663 | 0.047 | 0.136 | 98% | 14% | 46 | 7 | 0.8510 | 0.4080 |
| ontology | ONT | 3 | D Altchains | -0.0060578** | 0.0173163 | 0.044 | 0.127 | 90% | 21% | 10 | 5 | 0.0310 | 0.3590 |
| crypto.comchain | CRO | 7 | C Utility Token | -0.0060522 | 0.0633963 | 0.041 | 0.253 | 93% | 25% | 14 | 4 | 0.2740 | 0.4650 |
| usdcoin | USDC | 5 | C Stable Token | -0.011945*** | 0.0009457** | 0.005 | 0.005 | 0% | 9% | 1 | 11 | 0.0000 | 0.0410 |
| zcash | ZEC | 2 | D Altcoins | -0.0021012 | 0.0324938 | 0.056 | 0.325 | 98% | 27% | 54 | 4 | 0.2900 | 0.5590 |
| vsystems | VSYS | 3 | D Altchains | 0.0037974 | 0.0538087* | 0.029 | 0.150 | 84% | 42% | 6 | 2 | 0.3160 | 0.0730 |
| dogecoin | DOGE | 2 | D Altcoins | -0.0002922 | 0.5940562*** | 0.0729 | | 99% | 73% | 185 | 1 | 0.8570 | 0.0000 |
| vechain | VET | 3 | D Altchains | -0.0025973 | 0.0051919 | 0.034 | 0.118 | 93% | 22% | 15 | 5 | 0.2250 | 0.7050 |

*Notes: (*) significant at 10 %; (**) significant at 5%; (***) significant at 1%.*

Exhibit D.14: Table of regime switching tests Panel B

| | | | | coefficients | | volatility | | transition probabilities | | duration | | coefficients p-value | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Asset** | **Ticker** | **class** | **Name of asset class** | **mean.s1** | **mean.s2** | **stdev.s1** | **stdev.s2** | **p11** | **p21** | **d1** | **d2** | **1** | **mean.s2** |
| decred | DCR | 2 | D Altcoins | -0.0053018*** | 0.0282802*** | 0.039 | 0.126 | 90% | 19% | 10 | 5 | 0.0020 | 0.0090 |
| basicattention | BAT | 7 | C Utility Token | -0.0022064 | 0.0165592 | 0.056 | 0.121 | 97% | 8% | 30 | 13 | 0.4760 | 0.2160 |
| btcgold | BTG | 2 | D Altcoins | -0.0030301 | 0.0181693 | 0.052 | 0.242 | 99% | 8% | 97 | 13 | 0.1710 | 0.5260 |
| huobitoken | HT | 7 | C Utility Token | -0.0016286 | 0.0098729 | 0.023 | 0.079 | 76% | 27% | 4 | 4 | 0.3900 | 0.1130 |
| qtum | QTUM | 3 | D Altchains | -0.0040371* | 0.0276698 | 0.049 | 0.173 | 96% | 16% | 23 | 6 | 0.0570 | 0.1050 |
| hedgetrade | HEDGE | 6 | C Smart Token | 0.0047312 | 0.0337254* | 0.022 | 0.156 | 78% | 25% | 5 | 4 | 0.2860 | 0.0560 |
| egretia | EGT | 6 | C Smart Token | -0.0047012 | 0.0298026 | 0.043 | 0.142 | 82% | 25% | 6 | 4 | 0.2080 | 0.1520 |
| trueusd | TUSD | 5 | C Stable Token | -0.0098392*** | 0.001322*** | 0.000 | 0.008 | 8% | 12% | 1 | 9 | 0.0000 | 0.0000 |
| paxos | PAX | 5 | C Stable Token | -0.0098332*** | 0.0010483*** | 0.000 | 0.004 | 16% | 9% | 1 | 11 | 0.0000 | 0.0000 |
| omisego | OMG | 3 | D Altchains | -0.0031473 | 0.0597997 | 0.056 | 0.192 | 96% | 30% | 23 | 3 | 0.2280 | 0.1200 |
| kucoinshares | KCS | 7 | C Utility Token | -0.0048721 | 0.049013* | 0.056 | 0.178 | 98% | 7% | 59 | 15 | 0.2520 | 0.0900 |
| ravencoin | RVN | 3 | D Altchains | -0.0096588* | 0.0688689** | 0.055 | 0.164 | 92% | 38% | 12 | 3 | 0.0500 | 0.0330 |
| lisk | LSK | 3 | D Altchains | -0.0028345 | 0.0751836** | 0.053 | 0.331 | 98% | 15% | 46 | 7 | 0.1260 | 0.0230 |
| bitcoindiamond | BCD | 2 | D Altcoins | -0.0084282*** | 0.0666204 | 0.050 | 0.440 | 94% | 30% | 17 | 3 | 0.0010 | 0.2440 |
| nano | NANO | 2 | D Altcoins | -0.0071882** | 0.0775697*** | 0.066 | 0.214 | 97% | 11% | 32 | 9 | 0.0100 | 0.0010 |
| bittorrent | BTT | 6 | C Smart Token | -0.0053843 | 0.0309412 | 0.038 | 0.117 | 97% | 8% | 34 | 13 | 0.1450 | 0.1470 |
| energi | NRG | 3 | D Altchains | -0.0061731 | 0.0476469*** | 0.055 | 0.130 | 91% | 19% | 11 | 5 | 0.1480 | 0.0030 |
| educare | EKT | 6 | C Smart Token | -0.006254* | 0.1400407** | 0.065 | 0.316 | 94% | 57% | 18 | 2 | 0.0600 | 0.0260 |
| waves | WAVES | 3 | D Altchains | -0.0032362* | 0.0163568* | 0.044 | 0.126 | 95% | 11% | 21 | 9 | 0.0610 | 0.0510 |
| holo | HOT | 6 | C Smart Token | -0.0072599** | 0.0795159* | 0.055 | 0.167 | 94% | 40% | 16 | 3 | 0.0270 | 0.0510 |
| lambda | LAMB | 6 | C Smart Token | 0.0007776 | 0.1751017*** | 0.060 | 0.234 | 96% | 24% | 25 | 4 | 0.8940 | 0.0050 |
| hypercash | HC | 2 | D Altcoins | -0.0056271** | 0.0237828 | 0.044 | 0.188 | 88% | 33% | 8 | 3 | 0.0120 | 0.1430 |
| dai (sai) | SAI | 4 | D Stable Algorithmic | 0.000144 | 0.0033785 | 0.008 | 0.037 | 94% | 21% | 17 | 5 | 0.7450 | 0.4030 |
| bitusd | BITUSD | 4 | D Stable Algorithmic | | | | | | | | | | |
| sbd | SBD | 4 | D Stable Algorithmic | | | | | | | | | | |
| bitshares | BTS | 6 | C Smart Token | -0.0044005*** | 0.0277716*** | 0.040 | 0.141 | 94% | 19% | 16 | 5 | 0.0000 | 0.0040 |
| Digix Gold token | DGX | 5 | C Stable Token | -0.00000613 | 0.0026759 | 0.019 | 0.058 | 97% | 5% | 32 | 21 | 0.9960 | 0.5150 |
| **Market cap Index** | | | | | | | | | | | | | |
| Bitcoin Mcap | | | | 0.0014213 | 0.0024978*** | 0.066 | 0.017 | 87% | 8% | 8 | 12 | 0.5410 | 0.0000 |
| Altcoins Mcap | | | | | | | | | | | | | |
| Altchains Mcap | | | | | | | | | | | | | |
| Stable algo Mcap | | | | | | | | | | | | | |
| Stable token Mcap | | | | | | | | | | | | | |
| Smart token Mcap | | | | -0.0026526*** | 0.0227964*** | 0.030 | 0.143 | 95% | 18% | 21 | 6 | 0.0010 | 0.0030 |
| Utility token Mcap | | | | 0.0027166 | 0.007005 | 0.038 | 0.109 | 94% | 10% | 16 | 10 | 0.2050 | 0.4200 |
| TOTAL Crypto Mcap | | | | 0.0012163 | 0.0029392*** | 0.064 | 0.017 | 86% | 14% | 7 | 11 | 0.5970 | 0.0000 |

*Notes: (*) significant at 10 %; (**) significant at 5%; (***) significant at 1%.*

# E

# Glossary

**Blockchain**: A shared database between the nodes of a distributed ledger network where all past transactions are recorded in a chronological order.

**Consensus algorithm**: A mechanism that enables the distributed network to reach an agreement over the true state of the Blockchain, thus which transactions are valid.

**Crypto-exchanges**: Market makers that emerged to facilitate trade between cryptocurrencies.

**Distributed Ledgers**: A software that includes a shared database (the Blockchain) and a digital asset (the Cryptocurrency). The latter is optional.

**Fork**: A fork is a disagreement between nodes. If significant (e.g. over the protocol and the algorithm) this is called hard-fork. In a hard-fork the Blockchain results to a permanent divergence from the previous version of the Blockchain, though the latter still operates along the old path. This essentially creates two Blockchain, and the nodes who endorse the disagreement can upgrade to the new version while the others can continue to follow the old one. If not that significant, this is called soft-fork.

**Mining**: A fork is a disagreement between nodes. In case disagreement are significant (over the protocol and the algorithm) this is called hard-fork. If not that significant, this is called soft-fork.

**Node**: Any electronic devise that connects to the distributed ledger network whereby contribute and use resources. There are two types of nodes i.e. the full-node and the lightweight-node. Full-nodes form the backbone of the network for that they fully verify the rules enacted by the algorithm and the protocol of the distributed ledger. The requirement and downside is that the entire shared database need to be downloaded and continuously updated. In the latte case, the node does not download the shared database (Blockchain). Instead, can join the network and effectively rely upon full-nodes operations.

**Protocol**: The protocol describes the rules within the distributed ledger network. By way of example the determination of the supply schedule of cryptocurrencies (frequency, new units etc.) is written in the protocol.

**Satoshi Nakamoto**: The alias used by the unidentified person or group of persons who published a paper with the title “Bitcoin: A peer-to-peer electronic cash system” in 2008 upon which Bitcoin as open-source software as developed.